Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Advances in nondestructive techniques for quality and safety assessment of olive products using AI and big data analytics: A systematic review

Rania I.M. Almoselhy

raniaalmoselhy@arc.sci.eg

Agricultural Research Center

Nedyalko Katrandzhiev

University of Food Technologies

Meghit Boumediene Khaled

Djillali Liabès University

Imen Benchikh

Djillali Liabès University

Afreen Usmani

GMS College of Pharmacy

Mohd Aftab Siddiqui

Integral University

Rajakumari Rajendran

The Oxford College of Pharmacy

Manisha Bihani

Krupanidhi College of Pharmacy

Sabu Thomas

International and Inter University, Mahatma Gandhi University

Systematic Review

Keywords: artificial intelligence, big data analytics, computational pharmacology, hyperspectral imaging, nondestructive technology, olive products, quality and safety, spectroscopy

Posted Date: May 8th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9612429/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Advances in nondestructive techniques for quality and safety assessment of olive products using AI and big data analytics: A systematic review

Rania I.M. Almoselhy[1*], Nedyalko Katrandzhiev[2], Meghit Boumediene Khaled[3], Imen Benchikh[3], Afreen Usmani[4*], Mohd Aftab Siddiqui[5], Rajakumari Rajendran[6], Manisha Bihani[7], Sabu Thomas[8,9,10,11,12]

[1]Oils and Fats Research Department, Food Technology Research Institute, Agricultural Research Center, Giza, 12619, Egypt
[2]Faculty of Engineering, Department of Computer Systems and Technologies, University of Food Technologies, 26 Maritsa Blvd, Plovdiv, 4002, Bulgaria
[3]Laboratoire de Nutrition, Pathologie, Agro-Biotechnologie et Sante (Lab-NuPABS) Department of Biology, Faculty of Natural Sciences and Life, Djillali Liabès University, Sidi Bel Abbès, 22000, Algeria
[4]Department of Pharmacology, GMS College of Pharmacy, Amroha, 244221, India
[5]Faculty of Pharmacy, Integral University, Lucknow, Uttar Pradesh, 226026, India
[6]Department of Pharmaceutics, The Oxford College of Pharmacy, Bangalore, 560068, India
[7]Department of Pharmacognosy, Krupanidhi College of Pharmacy, Chikkabellandur, Bangalore, Karnataka, 560035, India
[8]International and Inter University Centre for Nanoscience and Nanotechnology, School of Energy Materials, and School of Nanoscience and Nanotechnology, School of Chemical Science, Mahatma Gandhi University, Kottayam, Kerala, 686560, India
[9]Department of Physics and Electronics, CHRIST (Deemed to Be University), Bengaluru, Karnataka, 560029, India
[10]Department of Chemical Sciences, University of Johannesburg, P.O. Box 17011, Doornfontein, 2028, Johannesburg, South Africa
[11]TrEST Research Park, TC-4/2322, GEM Building, Opposite College of Engineering Trivandrum, Kulathoor Rd, Sreekariyam, Trivandrum, Kerala, 695016, India
[12]Center of Excellence in Polymeric Materials for Medical Practice Devices, Department of Chemical Engineering, Faculty of Engineering, Chulalongkorn University, Bangkok, 10330, Thailand

***Correspondence:**
[*]**Rania I.M. Almoselhy,** raniaalmoselhy@arc.sci.eg; raniaalmoselhy@gmail.com
[*]**Afreen Usmani,** afreenusmaniu@gmail.com

1- **Rania I.M. Almoselhy** (raniaalmoselhy@arc.sci.eg; raniaalmoselhy@gmail.com)
2- **Nedyalko Katrandzhiev (**n_katrandzhiev@uft-plovdiv.bg**)**
3- **Meghit Boumediene Khaled (**boumedienemeghit.khaled@univ-sba.dz**)**
4- **Imen Benchikh (**imen.benchikh@univ-temouchent.edu.dz**)**
5- **Afreen Usmani** (afreenusmaniu@gmail.com)
6- **Mohd Aftab Siddiqui** (aftab.uzaiz@gmail.com)
7- **Rajakumari Rajendran** (rajimpharm@gmail.com)
8- **Manisha Bihani** (mmbihani@gmail.com)
9- **Sabu Thomas** (sabuthomas@mgu.ac.in)

Abstract

Background

Ensuring quality and safety of olive products is critical for consumer health, market value, and cultural heritage. Traditional destructive techniques are limited by their time-consuming and sample damage. Nondestructive techniques (NDT) allow real-time and non-invasive evaluation of authenticity, contamination, ripeness, and chemical composition. Artificial intelligence (AI) and big data analytics (BDA) integration enhances data interpretation, decision-making, and predictive modeling fostering transformative impact on olive industry.

Aims

This systematic review aimed to comprehensively evaluate advances in NDT for quality and safety assessment of olive products, emphasizing the role of AI and BDA and highlighting future prospects for industrial applications.

Methods

Following PRISMA guidelines, a systematic search was conducted across PubMed, Scopus, Web of Science, and Google Scholar, from 2010 to 2026 involving spectroscopic, imaging, sensor-based methods, integrated with AI and BDA.

Results

NDT like near-infrared and Raman spectroscopy, ultrasound, hyperspectral and X-ray imaging, and electronic nose/tongue enable rapid and accurate assessment of chemical composition, contamination, and ripeness. When coupled with AI algorithms, they significantly improve detection sensitivity, classification accuracy, and real-time monitoring. BDA facilitate comprehensive data management, predictive modeling, and supply chain traceability. Computational pharmacology contributes to understanding complex chemical interactions and bioactive compound behavior in olive products, enhancing safety and quality assessments. Challenges include data heterogeneity, lack of standardization, high instrumentation costs, interpretability of AI models, and regulatory hurdles.

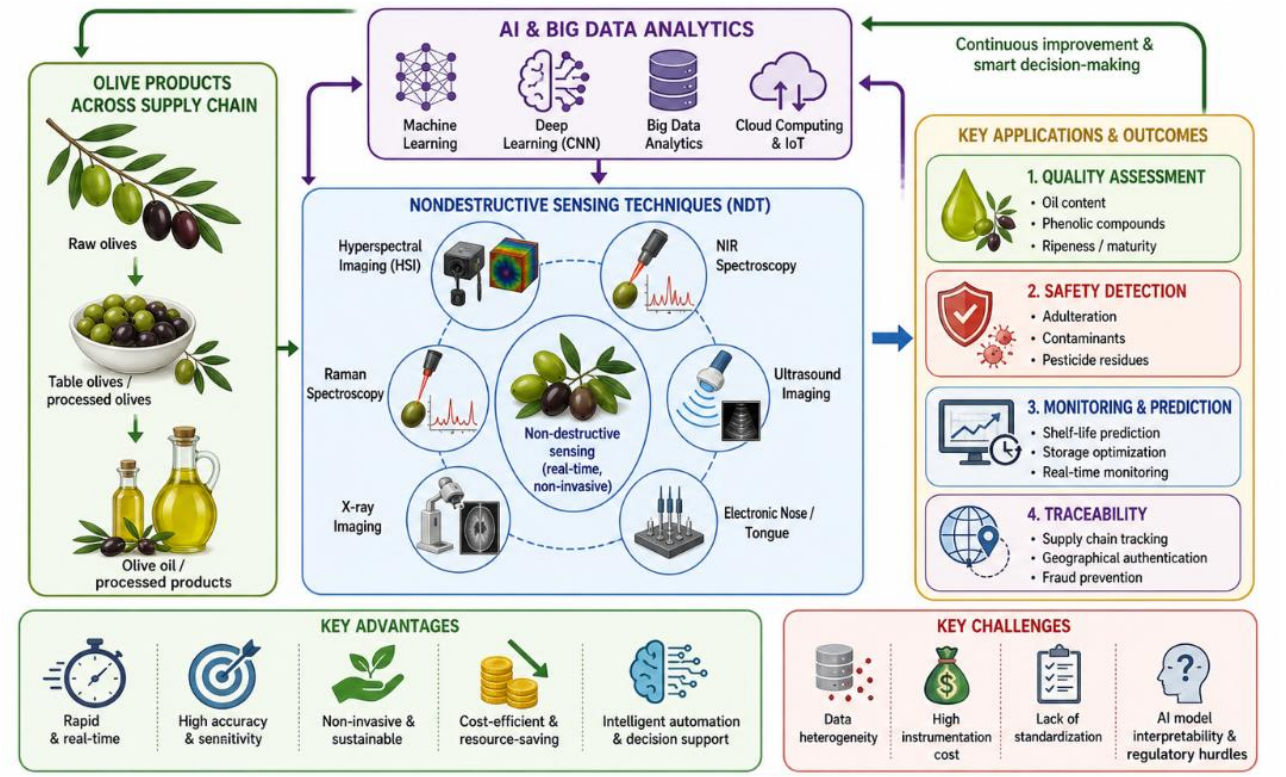
Conclusion

Integrating NDT with AI, BDA, and computational pharmacology offers a sustainable, efficient industrial pathway, with future research needed for standardization, portable device development, multi-sensor data fusion, and regulatory validation.

Keywords

artificial intelligence, big data analytics, computational pharmacology, hyperspectral imaging, nondestructive technology, olive products, quality and safety, spectroscopy

Graphical Abstract



1. Introduction

Olive products, especially olive oil and table olives, are important components of the Mediterranean diet and are gaining popularity worldwide due to their well-known health benefits, unique sensory attributes, and cultural importance [1]. The increasing worldwide demand for good quality olive products highlights the need for robust, reliable and efficient systems for the assessment of quality and safety at the production, processing and distribution stages [2].

Traditional assessment methods are mainly based on sensory evaluation, chemical analysis, and microbiological testing. These methods are accurate but labor intensive, time-consuming, destructive and require specialized facilities and personnel. Such limitations pose serious hindrances to timely decision making, quality control and customer safety, especially in large-scale industrial environments [3].

In recent years, technology has made great strides in the area of food quality and safety assessment, especially with the development and use of nondestructive techniques (NDT), which permit rapid, non-invasive evaluation of food products without damaging them and allow for continuous monitoring and quality control [4]. NIR spectroscopy, hyperspectral imaging (HSI), ultrasonic testing and computer vision systems have been extensively studied for their potential to identify adulteration, determine chemical composition, assess sensory attributes and detect contamination in olive products. These approaches offer several advantages, including minimal sample preparation, real-time analysis, and the ability to simultaneously assess multiple parameters [5].

However, the complexity of olive products and the diversity of quality parameters require extensive data processing tools, to understand the huge datasets generated by NDT techniques [6]. In this regard, artificial intelligence (AI) and big data analytics (BDA) have become game-changing technologies. Machine learning algorithms, deep learning models and advanced data processing techniques can identify meaningful patterns in large datasets, that can allow more accurate, consistent and automated quality assessment [7].

For instance, AI-enabled models have been successful in classifying the grades of olive oil, identifying adulteration, predicting the shelf life, and tracking the storage conditions [8]. Moreover, the integration of big data analytics allows to handle large data collected at different levels of the supply chain (SC), thus improving traceability, decision-making and predictive maintenance [9]. Despite these promising developments, the application of AI and big data analytics to nondestructive evaluation of olive products is a continuously evolving area [10].

A systematic review of the recent literature can yield useful findings of valuable insights into the state-of-the-art techniques, new trends and future prospects for research and industry adoption. Therefore, the aim of this work was to systematically evaluate the progress of NDT for the quality and safety assessment of olive products integrated with AI and big data analytics to highlight technological advances, assess their usefulness and discuss the problems and opportunities related to deployment. As the demand for high quality, safe and authentic olive products increases, the new technologies will be a triple win-win-win for producers, regulators and consumers.

2. Methodology

The current systematic review was accomplished in a rigorous methodological way using the evidence-based approach to ensure the inclusion of high-quality relevant published material, according to PRISMA guidelines applying the following steps:

2.1. Literature search strategy

A comprehensive search was conducted using several electronic databases with official online search engines, involving PubMed, Scopus, Web of Science, and Google Scholar. The search terms included “olive”, “quality and safety”, “nondestructive techniques”, “AI and big data analytics”, “spectroscopy”, and “hyperspectral imaging” among others. Boolean operations like AND, OR, and NOT were used to narrow the search results which were limited to English-language articles published in last 17 years, i.e. between 2010-2026.

2.2. Inclusion and exclusion criteria

The inclusion criteria included the well-documented peer-reviewed original research and review articles, with also screening the pertinent gray literature as high quality reports published outside the common academic publishing, extracted from potential theses, encyclopedias, pharmacopeias, herbal monographs, policy papers, government reports, and conference proceedings offering unique, and often unpublished viewpoints counting valuable information with reduced bias, that addressed the review's basic topics. The studies were screened and selected based on their significance, methodological rigor, and contributions to the field. The exclusion criteria included publications in other languages with inadequate data, non-peer-reviewed articles, and studies irrelevant to the main topics.

2.3. Selection process

All retrieved records were subjected to rigorous screening via a reference management system, with other manual screening for works not referenced, where duplicates were rejected. Two reviewers individually examined thoroughly the titles and abstracts to determine which articles were suitable and eligible for inclusion.

2.4. Data extraction and synthesis

Data from selected articles were extracted systematically and synthesized qualitatively. The results were presented comprehensively, with a focus on nondestructive techniques for quality and safety assessment of olive products. Data presentation was accomplished with all required schemes, flow diagrams, figures, and tables summarizing the findings in an informative, concise, and presentable manner.

3. Results and Discussion

3.1. Study selection

As illustrated (Fig. 1), the initial search generated 596,841 records. After removing duplicates, and ineligible records, 1500 unique records remained for subsequent screening where 300 reports sought for retrieval, from which 114 were included in review.

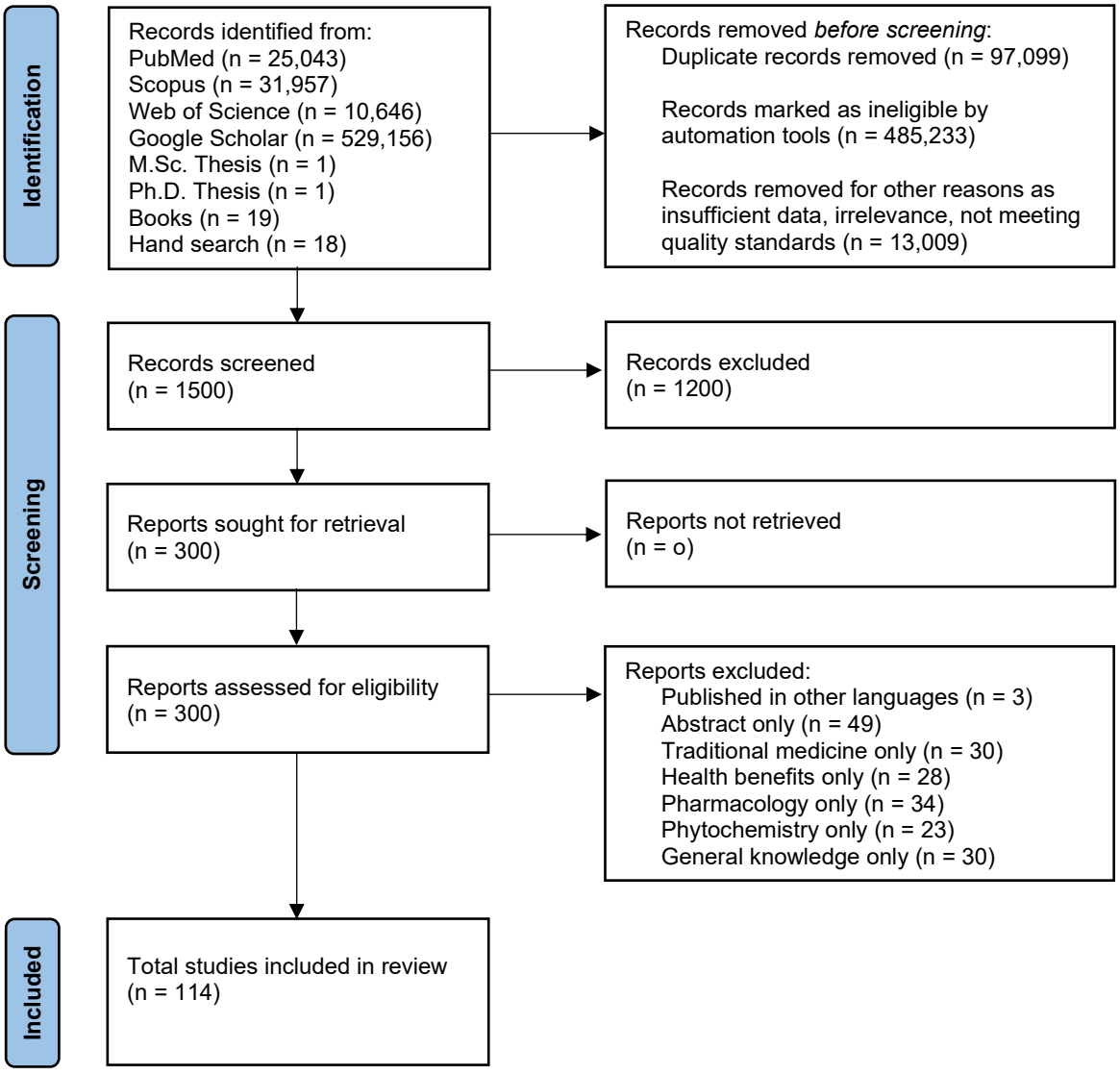


Fig. 1 PRISMA flow diagram including searches of databases and registers (2010-2026)

3.2. Overview of NDT for olive products

The increasing demand for high-quality and safe olive products has propelled the development and application of NDT in the olive industry. In the context of olive products, NDT techniques facilitate rapid, non-invasive assessment of parameters such as ripeness, oil content, contamination, and spoilage, often enhanced by advanced data analytics and artificial intelligence for accurate interpretation [11]. These techniques enable rapid, accurate, and cost-effective assessment of various quality and safety parameters without compromising the integrity of the products [12]. Nondestructive methods are particularly advantageous for real-time monitoring, large-scale screening, and ensuring compliance with safety standards, thereby facilitating better quality control and process optimization [13].

3.3. Definition and principles of NDT

NDT refers to a range of analytical techniques used to evaluate the properties of a material, component, or system without causing damage or impairing its future usefulness [14]. Unlike destructive testing methods, which involve damaging or destroying the sample to assess its characteristics, NDT aims to provide accurate information about the internal and surface quality of products while preserving their integrity [15]. This capability makes NDT particularly valuable in quality assurance, safety assessment, and process control across various industries, including food technology, aerospace, manufacturing, and infrastructure [16-18]. The fundamental principle of NDT is to detect anomalies, defects, or variations within a material or product by analyzing its physical, chemical, or biological properties through non-invasive methods [19]. These techniques often rely on the interaction of energy (such as electromagnetic radiation, sound waves, or thermal energy) with the tested object, with the resulting signals analyzed to infer the internal structure or composition [20].

Core principles of NDT include:

- **Non-invasiveness:** Ensuring the test does not alter or damage the product, maintaining its usability and safety [21].
- **Sensitivity:** The ability of the technique to detect small or subtle defects or variations within the material [22].
- **Reliability and Repeatability:** Providing consistent and reproducible results under similar conditions, essential for quality control processes [23].
- **Speed and Efficiency:** Allowing rapid assessment suitable for high-throughput environments, such as food processing lines [24].
- **Quantitative or Qualitative Analysis:** Offering measurable data (e.g., thickness, composition) or qualitative insights (e.g., presence of defects, spoilage) [25, 26].

3.4.Common NDT applied

NDT employed for assessing the quality and safety of olive products encompass a diverse array of spectroscopic, imaging, and acoustic modalities. These methods enable rapid, reliable, and non-invasive evaluation of various quality parameters, often integrated with artificial intelligence (AI) and big data analytics to enhance analytical accuracy and interpretability.

3.4.1. Spectroscopy techniques [Near-Infrared (NIR), Mid-Infrared (MIR), Raman]

Spectroscopy methods are extensively utilized in olive product analysis due to their rapidity and minimal sample preparation. Near-Infrared (NIR) spectroscopy measures overtones and combination bands of fundamental molecular vibrations, providing insights into moisture, oil content, and phenolic compounds. NIR's high penetration depth makes it suitable for bulk analysis of olives and olive oils. Mid-Infrared (MIR) spectroscopy offers more specific vibrational information, allowing detailed characterization of chemical constituents. Raman spectroscopy, based on inelastic scattering of monochromatic light, provides molecular fingerprints that aid in identifying adulteration, oxidation levels, and phenolic profiles. When coupled with chemometric algorithms and AI models, these spectroscopic techniques facilitate precise classification, quantification, and detection of adulterants in olive products [27-30].

3.4.2. Hyperspectral imaging

Hyperspectral imaging (HSI) combines traditional imaging and spectroscopy, capturing spatial and spectral data simultaneously. In olive quality assessment, HSI enables visualization of internal and surface attributes, detecting defects, bruises, and contamination. It allows for the mapping of chemical constituents such as oil content, moisture, and phenolics across the sample’s surface. The high-dimensional data generated are processed using machine learning algorithms for classification and anomaly detection, significantly improving the accuracy of quality grading and safety verification [31, 32].

3.4.3. X-ray fluorescence (XRF) and X-ray imaging

XRF spectroscopy provides qualitative and quantitative elemental analysis, which is valuable for detecting heavy metal contaminants or verifying geographic origin through trace element profiling. X-ray imaging techniques, including computed tomography (CT), offer detailed internal visualization of olive fruits, olive leaves, olive kernels and olive oil samples, revealing structural defects, foreign inclusions, or adulteration. These methods are non-invasive and provide high-resolution data essential for ensuring product integrity and compliance with safety standards [33, 34].

3.4.4. Ultrasound and acoustic methods

Ultrasound techniques utilize high-frequency sound waves to evaluate structural and compositional properties of olive products. In olive oil analysis, ultrasound can estimate viscosity, detect adulteration, and assess oxidation levels by monitoring acoustic impedance changes. Acoustic methods, including vibrational analysis, are employed to determine the firmness and ripeness of olives, facilitating harvest timing and quality grading. Integration with AI enhances the interpretation of complex acoustic signals, enabling real-time, non-destructive assessments [35-37].

3.4.5. Magnetic resonance imaging (MRI)

MRI offers detailed visualization of internal structures without physical sectioning. In olive product research, MRI can characterize the distribution of oil and water phases within olives, monitor oxidation processes, and detect internal defects or microbial contamination. Although less common due to higher operational costs, MRI provides comprehensive insights into the microstructural and compositional integrity of olive products, especially when combined with AI algorithms for pattern recognition and quantitative analysis [38, 39].

3.4.6. Electronic nose and tongue systems

Electronic nose and tongue systems mimic human sensory perception through sensor arrays capable of detecting volatile compounds and taste attributes. These devices facilitate rapid quality grading, detection of spoilage, and adulteration in olive oils and processed products, complementing traditional sensory evaluation [40].

The integration of these nondestructive techniques with advanced data analysis methods, such as machine learning and big data analytics, enhances their efficacy and reliability. Machine learning algorithms can interpret complex spectral and imaging data, improve classification accuracy, and enable predictive modeling for quality and safety assessment. Overall, the convergence of nondestructive sensing technologies with AI-driven analytics is revolutionizing the olive industry, promoting sustainable practices, and ensuring consumer safety [41-43].

3.5.Advantages over traditional methods

The integration of NDT with artificial intelligence (AI) and big data analytics (BDA) offers several significant advantages over conventional assessment methods in evaluating the quality and safety of olive products. Traditional methods, such as chemical analysis, sensory evaluation, and laboratory-based testing, although reliable, often involve labor-intensive procedures, longer turnaround times, and require destructive sampling, which can compromise the integrity of the product and limit real-time decision-making [42]. In contrast, the advanced approaches discussed in this review provide multiple benefits:

- **Non-destructive and rapid assessment:**

Nondestructive techniques such as near-infrared (NIR) spectroscopy, hyperspectral imaging, and electronic noses allow for the analysis of olive products without damaging samples. This facilitates real-time, on-site testing, significantly reducing the time required for quality and safety evaluation compared to traditional laboratory methods [32].

- **Enhanced accuracy and sensitivity:**

AI algorithms, including machine learning and deep learning models, can process complex datasets to identify subtle variations and patterns that are often undetectable through manual or conventional analytical techniques. This results in higher accuracy in detecting adulteration, spoilage, or contamination [44].

- **Cost-effectiveness:**

By enabling rapid screening and reducing the need for extensive laboratory consumables and personnel, these advanced methods decrease overall testing costs. The ability to perform high-throughput analysis also contributes to economic efficiency, especially in large-scale production settings [45].

- **Real-time monitoring and automation:**

The integration with big data analytics allows continuous monitoring of production processes, providing immediate feedback for quality control. Automated systems reduce human error and facilitate consistent assessments, leading to improved product uniformity and safety [46].

- **Environmental sustainability:**

NDT require minimal chemical reagents; these techniques align with environmentally sustainable practices. They reduce waste generation and energy consumption associated with traditional chemical analyses [47].

- **Broader data integration and predictive capabilities:**

Big data analytics (BDA) enable the synthesis of diverse data sources—spectral data, sensor outputs, historical records—fostering comprehensive insights. This enhances predictive modeling for shelf-life, spoilage risks, and optimal harvesting times, thereby supporting proactive decision-making [48].

- **Enhanced consumer confidence and compliance:**

Accurate, rapid, and reliable assessment methods bolster regulatory compliance and promote consumer trust by ensuring product safety and quality standards are consistently met. In conclusion, the adoption of AI-powered nondestructive techniques and big data analytics represents a transformative advancement over traditional assessment methods.

These innovations not only streamline quality and safety evaluation processes but also enhance accuracy, efficiency, and sustainability within the olive industry [49, 50].

3.6. Limitations and challenges

Despite the significant advancements in nondestructive techniques combined with AI and big data analytics for assessing the quality and safety of olive products, several limitations and challenges persist that may hinder widespread adoption and further development [51].

- **Data quality and availability:**

A major limitation is the scarcity of large, high-quality, and representative datasets necessary for training robust AI models. Variability in olive varieties, cultivation conditions, harvesting practices, and processing methods can introduce heterogeneity, making it difficult to develop generalized models. Moreover, data collection often requires extensive manual effort or sophisticated instrumentation, which can be costly and time-consuming.

- **Standardization and validation:**

The lack of standardized protocols for nondestructive testing methods and AI model validation poses challenges for comparability across studies and laboratories. Variations in sensor calibration, data preprocessing, and analytical procedures can lead to inconsistent results, impeding the establishment of universally accepted assessment criteria.

- **Sensor limitations and instrumentation costs:**

While nondestructive sensors such as hyperspectral imaging, near-infrared spectroscopy, and computer vision have shown promise, they often involve high initial investment costs, complex maintenance, and technical expertise for operation. Additionally, sensor limitations such as sensitivity to environmental conditions (e.g., lighting, temperature) can affect measurement accuracy.

- **Computational complexity and interpretability:**

Advanced AI models, particularly deep learning algorithms, require significant computational resources and expertise for development and deployment. Furthermore, their "black-box" nature can hinder interpretability, raising concerns among stakeholders about transparency and trustworthiness of the assessments.

- **Regulatory and ethical concerns:**

Implementation of AI-driven nondestructive testing methods must comply with food safety regulations and standards, which are still evolving in many regions. Ethical considerations regarding data privacy, ownership, and accountability also need to be addressed, especially when integrating big data analytics.

- **Integration into industry practices:**

Adapting these advanced techniques into existing production and quality control workflows can be challenging. Resistance to change, lack of technical training, and infrastructural limitations may slow down adoption in small and medium-sized enterprises.

- **Environmental and external factors:**

External factors such as environmental conditions, storage, and transportation can influence sensor readings and model predictions. Developing robust models that can account for such variability remains an ongoing challenge.

In conclusion, addressing these limitations and challenges requires collaborative efforts among researchers, industry stakeholders, and regulatory bodies. Future research should focus on improving data quality and standardization, developing cost-effective and user-friendly sensors, enhancing model transparency, and establishing regulatory frameworks to facilitate the broader application of nondestructive, AI-driven assessment techniques for olive products.

Table 1. summarizes the NDT, including the technique applied along with the parameters assessed with advantages and limitations and typical applications. Whereas, Table 2. summarizes the application domain of NDT with % accuracy.

Table 1. Summary of nondestructive techniques (NDT)

Technique	Principle	Parameters Assessed	Advantages	Limitations	Typical Applications	References
NIR, MIR, FTIR Spectroscopy	Molecular vibrations via near/mid-infrared light	Oil content, phenolics, moisture, functional groups	Rapid, minimal prep, portable	Sensitive to environmental factors	Olive oil quality, adulteration detection	52-57
Hyperspectral Imaging	Spectral + spatial data	Defects, contamination, chemical composition	Visual mapping, high accuracy	Data complexity, cost	Sorting, defect detection	58
Raman Spectroscopy	Inelastic scattering of monochromatic light	Adulterants, oxidation	Molecular fingerprinting	Cost, sensitivity	Authenticity, oxidation level	59
Ultrasound and E-nose	High-frequency sound waves	Structural defects, oil quality	Penetrates samples, real-time	Requires coupling medium	Ripeness, internal defects	36, 60, 61
MRI	Magnetic resonance signals	Oil/water distribution, internal defects	Detailed, non-invasive	Costly, slow	Microstructural analysis	62-64

Table 2. Application domains of NDT with %accuracy

Application Area	NDT Method	Key Findings	References
Adulteration detection	Hyperspectral Imaging	>95% accuracy	65
Ripeness classification	NIR Spectroscopy	92% accuracy	66
Pesticide residue detection	Raman + ML	Rapid detection	67
Storage monitoring	Sensors + AI	Real-time alerts	68

Critical appraisal of the comparative performance, validation status, and readiness levels of different techniques

In assessing the landscape of nondestructive techniques employed for olive product quality and safety assessment, it is imperative to critically compare their performance metrics, validation status, and overall readiness levels. Techniques such as near-infrared (NIR) spectroscopy, hyperspectral imaging, machine vision, and acoustic sensors have demonstrated varying degrees of efficacy in detecting parameters like chemical composition, adulteration, and spoilage [69].

- **Performance comparison:**

Numerous studies have reported high accuracy levels for hyperspectral imaging in identifying adulteration and quality grading, often exceeding 90% in classification tasks. NIR spectroscopy has shown promise in quantifying oil content and fatty acid profiles with comparable accuracy. Conversely, machine vision techniques excel in surface defect detection but may be limited in assessing internal quality attributes. AI-driven models, including deep learning algorithms, have enhanced predictive capabilities but are often contingent on large, high-quality datasets [32, 70, 71].

- **Validation Status:**

The validation of these techniques varies significantly (Table 3.). Many methods have been validated through laboratory-scale studies with limited external validation. For instance, hyperspectral imaging models often undergo internal cross-validation, but few have been validated across independent datasets or different production batches. Similarly, AI models require rigorous validation on diverse datasets to ensure robustness, which remains a challenge in current literature [72, 73].

- **Technology readiness levels (TRLs):**

Technology readiness levels (TRLs); a widely used approach, is a defining term for the readiness of new technology. It measures the technology maturity versus specific standards, ranging from level 1 (assigned for: concept) to level 9 (assigned for: market solution), as mentioned in Table 3 [74].

The technological readiness levels (TRLs) of NDT range from initial laboratory validation (TRL 3-4) to pilot-scale demonstrations (TRL 5-6). Although several techniques have transitioned into prototype development, widespread industrial adoption remains limited due to challenges in standardization, cost, and integration with existing processing lines. Notably, hyperspectral imaging and NIR spectroscopy are closer to TRL 7-8, with some commercial systems available, whereas advanced AI models are still primarily in the validation phase.

Table 3. Validation status and readiness levels

Technique	Validation Status	Datasets Used	TRL	Remarks	References
Hyperspectral Imaging	External validation	Multiple independent sets	7	Commercial systems available	74
NIR Spectroscopy	Internal validation	Laboratory data	6	Widely adopted in industry	74
Raman Spectroscopy	Pilot	Laboratory data	5	Portable devices emerging	74
Ultrasound	Laboratory	Specific samples	4	Field testing needed	74
MRI	Research	Controlled samples	3	Cost limiting	74

TRL: Technology Readiness Level

- **Emerging technologies & future pathways in NDT**

Emerging technologies and future pathways in NDT (Table 4) are transforming the approach that industries assess the integrity and safety of materials and structures. Innovations such as terahertz spectroscopy, portable sensors, Internet of Things (IoT) integration, and advanced data fusion algorithms are enabling more accurate, rapid, and comprehensive evaluations. These advancements promise to enhance defect detection capabilities, facilitate on-site assessments, and enable continuous monitoring, ultimately leading to more reliable and efficient nondestructive inspection processes. As research and development continue to progress, these emerging technologies hold significant potential to shape the future landscape of NDT [75-78].

Table 4. Emerging technologies & future pathways in NDT

Technology / Strategy	Description	Potential Impact	Development Stage	References
Terahertz Spectroscopy	High-frequency analysis	Detects deeper defects	Early research	75
Portable Sensors	Handheld spectrometers	On-site rapid assessment	Prototype level	76
IoT Integration	Wireless data collection	Continuous monitoring	Pilot projects	77
Data Fusion Algorithms	Multi-sensor data integration	Holistic evaluation	Developing	78

3.7. AI and big data analytics in food quality and safety assessment

The rapid advancement of artificial intelligence (AI) and big data analytics (BDA) has revolutionized the food quality and safety assessment, offering unprecedented capabilities in data processing, pattern recognition, and predictive modeling. These technologies facilitate real-time monitoring, accurate classification, and early detection of contaminants or quality deviations, thereby ensuring product integrity and consumer safety [79-81].

Fig. 2 shows the integration of nondestructive techniques, including near-infrared spectroscopy, hyperspectral imaging, and electronic nose systems, with artificial intelligence and big data analytics for olive quality evaluation. The framework highlights how multi-sensor data are processed through AI-driven models to enable rapid, non-destructive assessment of quality grading, adulteration detection, freshness, and safety.

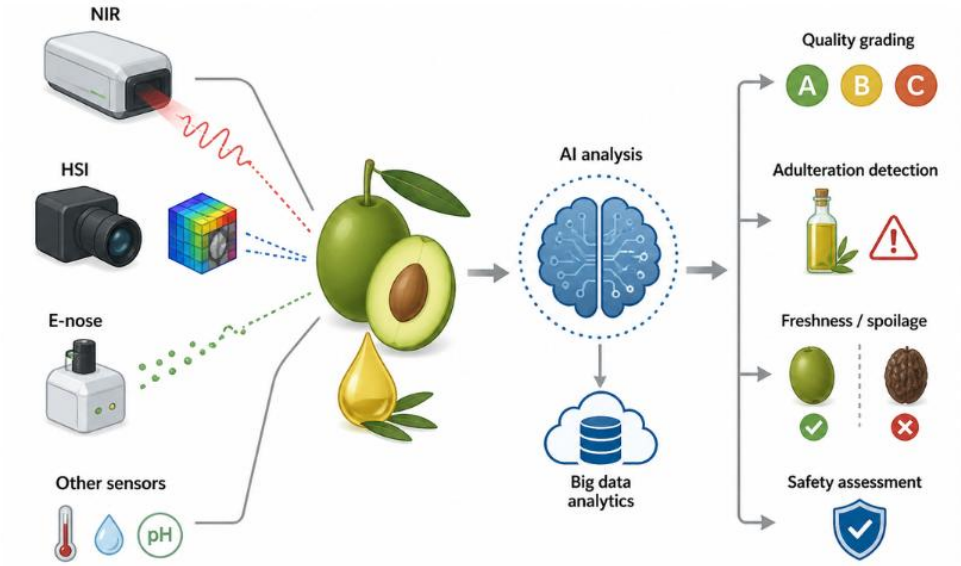


Fig. 2 AI/BDA-integrated NDT for quality and safety assessment of olive products

3.7.1. Overview of AI techniques used in olive products assessment

The application of Artificial Intelligence (AI) in the nondestructive assessment of olive products (Table 5) has witnessed significant advancements, primarily leveraging various machine learning algorithms and data analysis techniques. These AI methodologies facilitate rapid, accurate, and noninvasive evaluation of quality and safety parameters, thus enhancing the efficiency of quality control processes. AI encompasses various computational techniques, including machine learning (ML), deep learning (DL), and natural language processing (NLP), which have been increasingly employed in olive product evaluation. Machine learning algorithms such as support vector machines (SVM), random

forests, and neural networks have demonstrated high accuracy in predicting olive oil quality parameters, such as free fatty acids, peroxide value, and sensory attributes, based on spectroscopic and chromatographic data. For instance, convolutional neural networks (CNNs) have been utilized for image-based classification of olive fruit ripeness and detection of defects or adulteration. Deep learning models excel in handling complex, high-dimensional datasets and automating feature extraction, reducing reliance on human expertise. These models can analyze multispectral imaging, near-infrared spectroscopy (NIRS), and hyperspectral data to classify olive oils by origin, grade, and authenticity with high precision. Furthermore, AI-driven algorithms enable predictive maintenance of processing equipment and optimize harvest and processing conditions to enhance product quality [82-85].

3.7.1. Machine learning algorithms

Machine learning (ML) algorithms are mathematical sets of rules or instructions that allow computers to learn patterns from data to make predictions or decisions without being explicitly programmed for a specific task. ML includes the following:

3.7.1.1. Support vector machines (SVM)

SVMs have been widely adopted due to their robustness in classification tasks involving complex, high-dimensional data. In olive product assessment, SVMs have been employed to classify olive oil based on geographical origin, detect adulteration, and predict quality grades by analyzing spectral data obtained from techniques such as near-infrared (NIR) and visible spectroscopy [82].

3.7.1.2. Artificial neural networks (ANN)

ANN models mimic biological neural networks and are particularly effective in modeling nonlinear relationships within data. They have been utilized for predicting chemical constituents, sensory qualities, and identifying contamination in olive oils. Their ability to learn from large datasets makes them suitable for handling complex spectral and image data [83].

3.7.1.3. Random forest (RF)

RF algorithms, an ensemble learning method based on decision trees, offer high accuracy and interpretability. In olive quality assessment, RF models have been used to classify olive ripeness stages, detect adulterants, and predict oxidative stability by analyzing multiple data sources, including spectral, chemical, and visual attributes [84].

3.7.1.4. Deep learning (DL)

Deep learning architectures, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have gained prominence due to their capacity to automatically extract hierarchical features from raw data. CNNs, in particular, have proven effective in image-based analyses, including grading olives, detecting defects, and classifying olive oil quality through visual and spectral imaging [85].

Table 5. AI techniques used in olive products assessment

Algorithm	Type	Applications	Strengths	Challenges	References
SVM	Supervised	Adulteration detection, origin classification	High accuracy, handles high-dimensional data	Kernel selection	82
ANN	Supervised	Quality prediction, contamination	Nonlinear modeling	Overfitting risk, interpretability	83
RF	Supervised	Ripeness, spoilage, classification	Good accuracy, interpretability	Parameter tuning	84
Deep learning CNN	Supervised	Image-based grading, defect detection	Hierarchical features, high performance	Computationally intensive	85

3.7.1.5. Data mining and pattern recognition

Data mining techniques facilitate the extraction of meaningful patterns and relationships from large and complex datasets acquired during nondestructive testing. Pattern recognition algorithms enable the identification of characteristic signatures associated with specific quality and safety attributes. For instance, clustering algorithms have been employed to group olive samples based on physicochemical properties, while association rule mining has uncovered correlations between spectral features and contamination levels. These AI techniques collectively contribute to building predictive models that enhance the accuracy and reliability of nondestructive assessments. They also support the development of real-time monitoring systems, thereby promoting safer and higher-quality olive products in the industry [86-88].

3.7.2. Overview of big data analytics (BDA) in olive products assessment

The integration of big data analytics involves processing vast and heterogeneous datasets generated from sensors, IoT devices, laboratory tests, and supply chain records. Such data include climatic variables, soil conditions, harvesting times, processing parameters, and market information. Big data platforms facilitate data storage, management, and advanced analytics, providing comprehensive insights into factors affecting olive product quality and safety. Advanced analytics techniques, such as data

mining, clustering, and correlation analysis, help identify patterns and relationships that influence product attributes. For example, combining environmental data with quality parameters can enable predictive models for optimal harvest timing and storage conditions. Additionally, big data analytics support traceability and authentication efforts by integrating supply chain information, thereby combating fraud and adulteration [89].

3.7.2.1. Handling large datasets from NDT methods

Olive product evaluation generates vast amounts of data from various NDT modalities such as hyperspectral imaging, near-infrared spectroscopy, and multispectral imaging. BDA facilitates the efficient management, storage, and processing of these heterogeneous datasets. Through scalable data architectures and cloud-based platforms, it enables the integration of diverse data types, including spectral, visual, and sensor-based information, ensuring comprehensive analysis. This capacity to handle large datasets minimizes data loss and supports the development of robust models for quality and safety assessment [90].

3.7.2.2. Enhancing prediction accuracy

By leveraging advanced algorithms such as machine learning and deep learning within big data frameworks, the accuracy of predictive models is significantly improved. These models can identify subtle patterns and correlations within extensive datasets that traditional methods might overlook. Consequently, predictive analytics enhances classification accuracy for detecting adulteration, spoilage, and contamination, and predicts quality parameters like polyphenol content, ripeness level, and oxidative stability with higher precision. This leads to more reliable assessments, reducing false positives and negatives [91].

3.7.2.3. Real-time monitoring and decision-making

Big data analytics enables real-time data processing and analysis, which is crucial for prompt decision-making in the supply chain and processing facilities. Continuous data streams from NDT sensors can be monitored instantaneously, allowing for immediate detection of quality deviations or safety hazards. This capability supports dynamic quality control, reduces waste, and ensures compliance with safety standards. Additionally, real-time analytics facilitates adaptive process control, optimizing production parameters to maintain product integrity and safety throughout the supply chain [91].

3.7.2.4. Enhanced data acquisition and processing:

NDT such as hyperspectral imaging, near-infrared spectroscopy, and ultrasonic testing generate vast amounts of high-dimensional data. When combined with AI algorithms, particularly machine learning and deep learning models, these data can be processed efficiently to identify complex patterns and subtle anomalies that are often imperceptible to

traditional analysis. Big data infrastructure ensures the storage, management, and real-time processing of these large datasets, facilitating continuous monitoring and assessment [91].

3.7.2.5. Improved accuracy and reliability:

AI models trained on extensive datasets can improve predictive accuracy and robustness in quality and safety evaluations. For example, machine learning algorithms can classify olive oil samples based on their chemical composition or detect adulteration with high precision. The large volume of data handled by big data systems enhances the models' generalizability across different batches, harvests, and environmental conditions, reducing false positives and negatives [91].

3.7.2.6. Real-time monitoring and decision support:

The synergy enables real-time or near-real-time assessment of olive products throughout the supply chain. IoT sensors integrated with NDT methods can feed data into AI-driven analytics platforms, providing instant insights for producers and regulatory bodies. This capability supports proactive decision-making, rapid response to contamination events, and improved traceability [91].

3.8. Synergy between NDT, AI, and BDA

The synergy between AI and BDA enhances the capacity for holistic assessment of olive products. Machine learning models trained on large datasets can deliver robust, scalable, and accurate decision-making tools. Moreover, cloud computing platforms enable real-time data processing and remote monitoring, facilitating rapid response to potential safety issues. The integration of NDT, AI, and BDA represents a transformative approach in the assessment of olive product quality and safety. This synergy leverages the strengths of each component to overcome traditional limitations, enabling more accurate, rapid, and comprehensive evaluations [91].

3.9. Cost-effectiveness and scalability

Automating quality assessment processes through AI and BDA reduces reliance on labor-intensive laboratory analyses, lowering costs and increasing scalability. The ability to analyze large datasets across multiple parameters simultaneously enhances comprehensive quality control, ensuring safety standards are consistently met [91].

3.10. Challenges and future directions

Despite their promising applications, several challenges hinder the widespread adoption of AI and BDA in olive product assessment. These include data quality and standardization issues, high computational costs, and the need for specialized expertise. Future research should focus on developing standardized protocols, accessible platforms,

and integrated systems that combine AI and big data analytics to further enhance the efficiency, reliability, and sustainability of olive product quality control.

While the synergy offers significant advantages, challenges such as data heterogeneity, standardization, and the need for large, annotated datasets persist. Future research should focus on developing interoperable platforms, improving AI model interpretability, and establishing standardized protocols for data collection and analysis.

In summary, the synergistic integration of NDT, AI, and big data analytics holds immense potential to revolutionize the quality and safety assessment of olive products. By harnessing these technologies' combined power, stakeholders can achieve more accurate, efficient, and proactive management of olive product quality, ensuring consumer safety and product excellence.

Fig. 3 presents a streamlined workflow integrating nondestructive techniques with artificial intelligence and big data analytics for comprehensive evaluation of olive products. The framework demonstrates how multi-source data are processed through machine learning and deep learning models to enable accurate prediction, real-time monitoring, and reliable assessment of quality, authenticity, freshness, and safety.

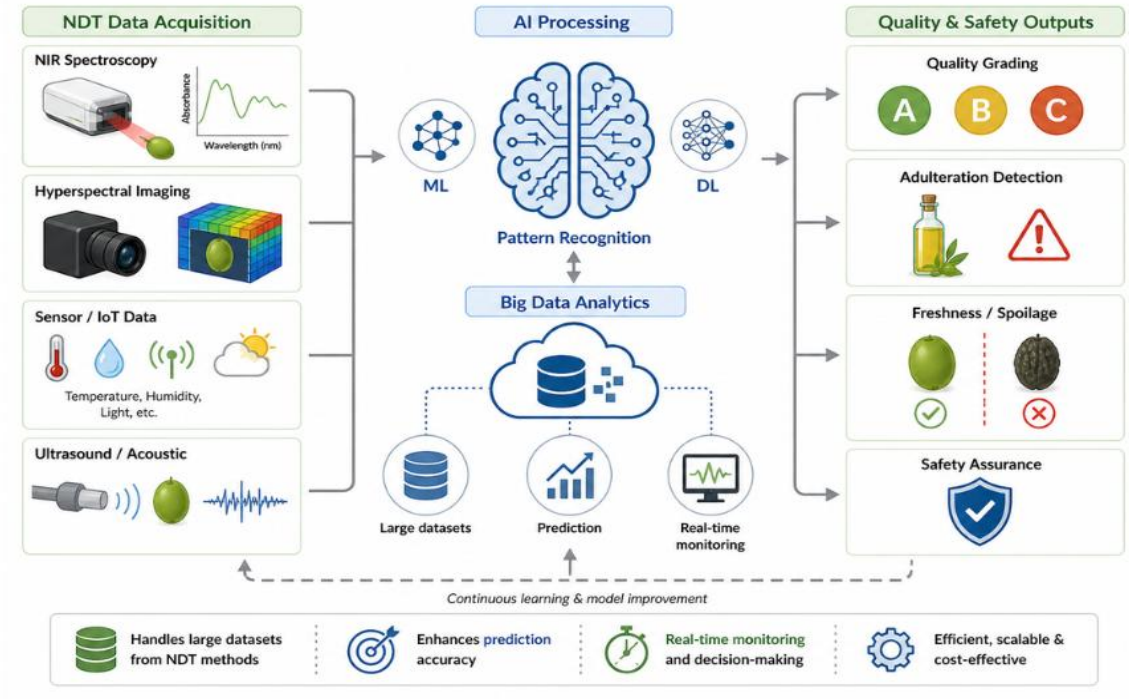


Fig 3. Integrated framework of NDT, AI, and BDA for quality and safety assessment of olive products

3.11. Computational pharmacology of olive products

Computational pharmacology is an interdisciplinary field that employs computational methods and models to elucidate the biological activities, mechanisms of action, and therapeutic potentials of natural products, including those derived from olives. Olive products, particularly olive oil, are rich in bioactive compounds such as phenolic acids, secoiridoids, flavonoids, and lignans. These constituents have been extensively associated with various health benefits, including anti-inflammatory, antioxidant, cardioprotective, and anticancer effects, making them prime candidates for pharmacological exploration [92-95].

3.11.1. Bioactive compounds and their pharmacological significance

Key phenolic constituents like hydroxytyrosol, oleuropein, and tyrosol have attracted significant scientific attention due to their potent biological activities. Hydroxytyrosol, for example, exhibits strong free radical scavenging capabilities, contributing to its antioxidant properties. Oleuropein possesses anti-inflammatory and cardioprotective effects, partly through modulation of inflammatory mediators and oxidative stress pathways. Tyrosol also demonstrates anti-inflammatory and neuroprotective activities. Understanding the molecular interactions, pharmacokinetics, and metabolism of these compounds is crucial for harnessing their full therapeutic potential and developing effective nutraceutical formulations [96-102].

3.11.2. Role of computational techniques

Computational pharmacology utilizes a variety of in silico tools—including molecular docking, molecular dynamics (MD) simulations, quantitative structure-activity relationship (QSAR) modeling, and network pharmacology—to explore for example how olive-derived compounds interact with biological targets. These approaches facilitate the identification of potential protein targets, predict bioavailability, and evaluate toxicity profiles, thereby streamlining the early phases of drug discovery and development [103].

3.11.3. Molecular docking and target identification

Molecular docking studies have been extensively used to simulate the binding affinity and mode of olive phenolics to key enzymes and receptors involved in inflammation, oxidative stress, and carcinogenesis. For instance, docking analyses reveal how hydroxytyrosol interacts with cyclooxygenases (COX-1 and COX-2), providing insights into its anti-inflammatory effects. Similarly, oleuropein's interactions with signaling proteins such as NF-κB and other transcription factors help elucidate its role in modulating inflammatory and apoptotic pathways. These studies contribute valuable hypotheses for subsequent experimental validation [104, 105].

3.11.4. Network pharmacology and multi-target effects

Given the complex and multifaceted actions of phytochemicals, network pharmacology approaches are instrumental in exploring the multi-target interactions of olive bioactives. By constructing interaction networks linking compounds to their molecular targets and associated pathways, researchers can identify synergistic effects and elucidate mechanisms underlying their health benefits. Such integrative analyses support the development of multi-target therapeutics and functional foods with broad-spectrum efficacy [94].

3.11.5. Pharmacokinetics and toxicology predictions

In silico ADMET (Absorption, Distribution, Metabolism, Excretion, and Toxicity) models are valuable tools for predicting the pharmacokinetic profiles and safety of olive bioactives. These computational assessments guide formulation strategies, optimize dosing regimens, and identify compounds with favorable safety margins. Early prediction of toxicity and bioavailability accelerates the translation of natural products into clinical and nutraceutical applications, reducing reliance on costly experimental testing [106-109].

3.11.6. Future perspectives

Advancements in computational pharmacology promise to revolutionize personalized nutrition and medicine by enabling tailored interventions based on individual genetic profiles and microbiome compositions. Integrating computational insights with experimental validation can facilitate the development of novel nutraceuticals, functional foods, and therapeutic agents derived from olives. Such approaches hold significant potential for preventive healthcare, management of chronic diseases, and promotion of healthy aging, aligning with the growing trend toward precision health strategies [110-114].

3.12. Relationship between NDT and computational pharmacology of olive products

Both the field of computational pharmacology and the advancements in NDT for quality and safety assessment employ cutting-edge AI and BDA to optimize the utilization of olive products for health and safety purposes. Their relationship is multifaceted and synergistic (Table 6). In summary, the integration of computational pharmacology with AI, BDA, and NDT creates a comprehensive framework for both ensuring the safety and authenticity of olive products and unlocking their full therapeutic potential. Together, these approaches support the development of high-quality, effective, and safe olive-based nutraceuticals and pharmaceuticals, advancing both public health and scientific understanding.

Table 6. Relationship between NDT and computational pharmacology of olive products

Parameter	Nondestructive techniques (NDT)	Computational pharmacology
Shared use of AI and BDA	Nondestructive Techniques employ AI algorithms and big data analytics to analyze spectral, imaging, or sensor data for rapid, accurate assessment of the quality, authenticity, and safety of olive products.	Computational Pharmacology uses AI-driven modeling, molecular simulations, and data analytics to predict the biological activities, target interactions, and pharmacokinetic profiles of olive-derived bioactive compounds.
Data integration and holistic understanding	The data generated from nondestructive assessments (e.g., spectral data indicating chemical composition) can inform pharmacological models by providing real-time, detailed compositional information.	Conversely, pharmacological data about bioactive compounds can guide the development of targeted nondestructive tests aimed at detecting these specific compounds or their biomarkers, ensuring the presence of therapeutically relevant constituents.
Enhancing product safety and therapeutic efficacy	Nondestructive techniques ensure the safety and quality of olive products during processing and storage, minimizing contamination or degradation of bioactive compounds.	Computational pharmacology helps understand how variations in composition (detected through nondestructive testing) influence biological activity, enabling better formulation and quality control for health-promoting products.
Accelerating research and development	Combining AI-driven quality assessment with pharmacological predictions accelerates the identification of promising olive extracts or compounds for therapeutic use, streamlining the pathway from raw material to clinical application.	
Personalized nutrition and medicine	Insights from pharmacology can inform personalized dietary recommendations based on product quality, while nondestructive assessment ensures these recommendations are based on authentic, high-quality products.	

Fig. 4 illustrates the bidirectional integration between AI-driven NDT and computational pharmacology for comprehensive evaluation of olive products. It highlights how compositional data derived from NDT inform pharmacological modeling, while computational insights guide targeted quality assessment, enabling improved therapeutic efficacy, safety, and product optimization.

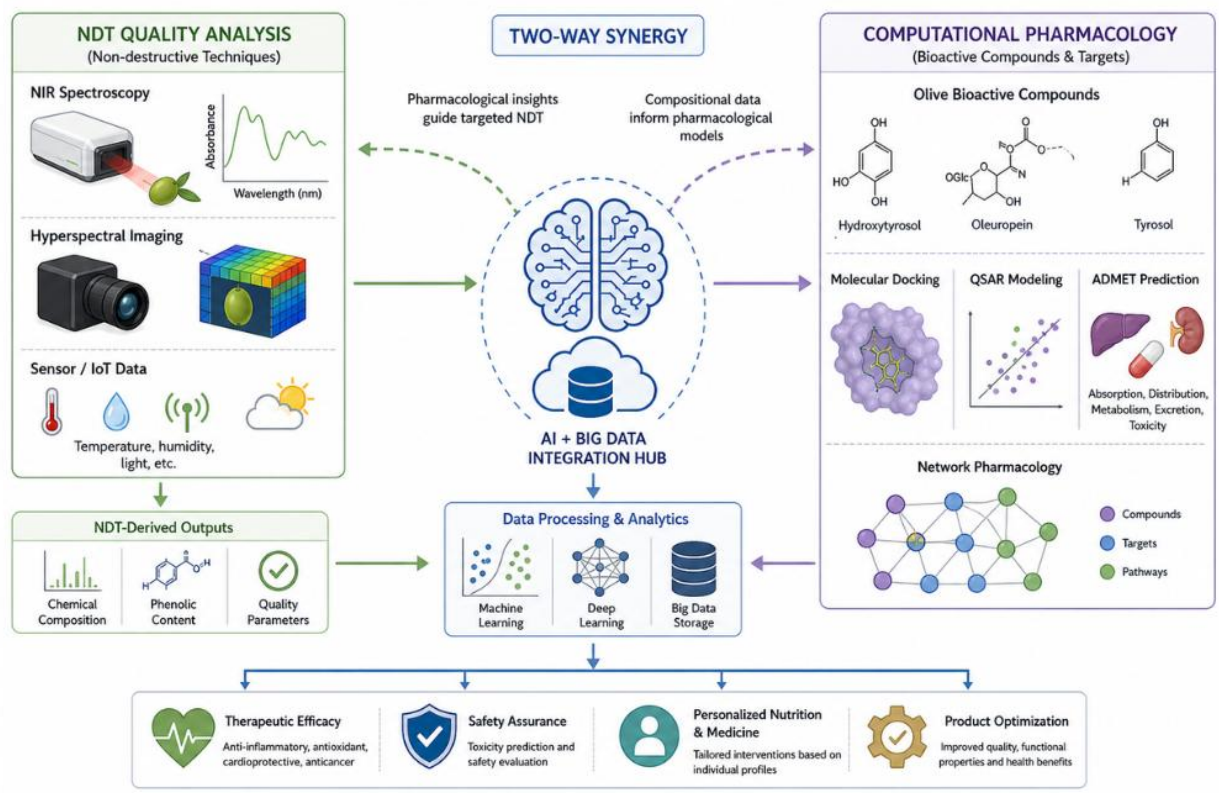


Fig. 4 Synergistic integration of NDT and computational pharmacology in olive product analysis

3.13. Applications and case studies

The integration of NDT with AI and BDA has revolutionized the assessment of olive products, enabling rapid, accurate, and non-invasive evaluation of quality and safety parameters. This section explores various application domains and highlights key case studies illustrating the effectiveness of these approaches.

3.13.1. Quality assessment of olive oil

Ensuring authentic and high-quality olive oil is paramount for consumer safety and market value. AI-driven NDT methods such as near-infrared (NIR) spectroscopy, hyperspectral imaging, and Raman spectroscopy have been employed to detect adulteration, quantify acidity levels, and assess phenolic content. For instance, Aqeel et al. [65] utilized hyperspectral imaging combined with machine learning classifiers (SVM and CNN) to accurately identify adulterated olive oils with a detection accuracy exceeding 95%. Similarly, NIR spectroscopy coupled with partial least squares regression (PLSR) has been effective in quantifying phenolic compounds, indicators of antioxidant properties.

3.13.2. Safety assessment

Food safety concerns, including pesticide residues and microbial contamination, have prompted the development of nondestructive safety evaluation techniques. AI-enhanced spectroscopic methods have demonstrated proficiency in detecting pesticide residues rapidly. For example, Thuku et al. [67] applied Raman spectroscopy with deep learning models to identify pesticide residues at levels below regulatory thresholds. Microbial contamination, such as molds or pathogens, has been monitored using hyperspectral imaging combined with AI algorithms that classify microbial presence with high sensitivity. These methods facilitate on-site safety assessments, reducing reliance on laboratory-based analyses.

3.13.3. Freshness and ripeness determination in olives

Accurate determination of olive ripeness and freshness is critical for harvest timing and processing. NIR spectroscopy integrated with AI models has shown promising results in classifying olives based on ripeness stages. A case study [66] employed support vector machines (SVM) to distinguish between different ripening stages with an accuracy of 92%. Such approaches enable farmers and producers to optimize harvest schedules and ensure optimal product quality.

3.13.4. Storage condition monitoring

Maintaining optimal storage conditions prolongs the shelf life and preserves the quality of olive products. Sensor-based NDT methods, coupled with AI analytics, have been deployed to monitor parameters such as temperature, humidity, and ethylene concentration. For example, a study [68] utilized IoT sensors and machine learning algorithms to detect deviations from ideal storage conditions in real-time, enabling prompt corrective actions. These systems improve supply chain management and reduce post-harvest losses.

3.13.5. Comparison of different NDT-AI approaches

Various NDT techniques have been integrated with AI, each with distinct advantages and limitations. Hyperspectral imaging offers comprehensive spectral information suitable for multi-parameter assessments but requires complex data processing. Raman and NIR spectroscopy are rapid and portable, ideal for field applications but may have limitations in sensitivity to certain contaminants. Machine learning algorithms such as SVM, Random Forest, and deep neural networks differ in complexity, interpretability, and accuracy. Comparative analyses across studies indicate that deep learning models generally outperform traditional classifiers in handling high-dimensional spectral data, albeit at the expense of increased computational requirements.

3.13.6. Summary of key findings from selected studies

- AI-enhanced NDT techniques provide highly accurate, rapid, and non-invasive assessment of olive oil quality parameters, including adulteration and phenolic content.
- Spectroscopic methods combined with AI enable effective detection of pesticide residues and microbial contamination, supporting food safety.
- Integration of NIR spectroscopy and AI models facilitates precise ripeness classification, aiding harvesting decisions.
- Sensor networks and machine learning algorithms for storage monitoring improve post-harvest management.
- Deep learning approaches generally outperform traditional machine learning models in analyzing complex spectral data, though they demand greater computational resources.

Overall, the convergence of nondestructive testing, AI, and big data analytics holds significant promise for advancing the quality and safety assurance of olive products, fostering sustainable and efficient production systems.

3.14. Current challenges and limitations

Despite significant advancements in nondestructive techniques for assessing the quality and safety of olive products using AI and big data analytics, several challenges and limitations persist that hinder widespread adoption and optimal performance.

3.14.1. Technical challenges in implementing NDT

Implementing nondestructive techniques such as spectroscopy, imaging, and sensor technologies requires sophisticated instrumentation and expertise. These methods often demand precise calibration and maintenance to ensure consistent accuracy. Additionally, the integration of these technologies into existing processing lines can be complex, requiring customized solutions tailored to specific olive products and processing conditions. Variability in environmental factors, such as temperature and humidity, can also affect the reliability of measurements, posing further technical hurdles.

3.14.2. Data variability and standardization issues

Data collected from nondestructive methods often exhibit high variability due to differences in olive varieties, ripeness stages, harvesting conditions, and processing methods. This heterogeneity complicates the development of robust models capable of generalizing across diverse datasets. Furthermore, the lack of standardized protocols for data acquisition, preprocessing, and analysis hampers comparability between studies and limits the reproducibility of results, undermining confidence in AI-driven assessments.

3.14.3. AI model interpretability and robustness

While AI models, particularly deep learning algorithms, have demonstrated remarkable predictive capabilities, their interpretability remains a concern. The "black box" nature of many models makes it difficult for practitioners to understand the underlying decision-making processes, which can impede trust and acceptance. Additionally, models may suffer from overfitting and reduced robustness when exposed to new or unseen data, especially if training datasets are limited or unrepresentative of real-world variability.

3.14.4. Cost and scalability considerations

The deployment of advanced nondestructive sensors and AI systems often entails considerable upfront investment, including equipment costs, system integration, and personnel training. These expenses can be prohibitive for small and medium-sized enterprises. Scalability also poses challenges; methods that perform well in laboratory or pilot settings may not translate seamlessly to large-scale industrial applications due to differences in throughput, environmental conditions, and resource availability.

3.14.5. Regulatory and acceptance barriers

Regulatory frameworks governing food safety and quality assessment vary across regions and are often stringent. The integration of AI-driven nondestructive techniques into official inspection processes may require extensive validation and certification, which can be time-consuming and costly. Moreover, stakeholder acceptance—ranging from producers and regulators to consumers—may be limited by skepticism toward automated systems and concerns about data privacy, traceability, and transparency.

3.15. Future perspectives and recommendations

The rapid evolution of nondestructive testing (NDT) technologies, coupled with advancements in artificial intelligence (AI) and big data analytics, presents significant opportunities to enhance the quality and safety assessment of olive products. Future research and development should focus on several key areas to realize the full potential of these emerging tools.

3.15.1. Emerging technologies and innovations

Emerging technologies such as hyperspectral imaging, terahertz spectroscopy, and portable Raman sensors are poised to revolutionize olive product evaluation by providing rapid, high-resolution, and non-invasive analyses. Integration of these modalities with advanced AI algorithms can facilitate real-time detection of adulteration, spoilage, and quality parameters, thereby improving robustness and accuracy.

3.15.2. Integration of IoT with NDT, AI, and Big Data

The Internet of Things (IoT) offers promising avenues for continuous, remote monitoring of olive cultivation, harvesting, and processing environments. Embedding IoT sensors with NDT devices and AI analytics can enable real-time data collection and interpretation across the supply chain, fostering predictive maintenance, quality control, and traceability. This integration can significantly reduce delays and human errors, leading to more resilient and transparent systems.

3.15.3. Standardization and validation of methods

To facilitate widespread industrial adoption, establishing standardized protocols and validation frameworks for NDT techniques combined with AI and big data is imperative. International collaboration should aim to develop universally accepted benchmarks, calibration standards, and performance metrics to ensure consistency, reliability, and comparability of results across different laboratories and regions.

3.15.4. Developing portable and affordable devices

The development of compact, user-friendly, and cost-effective NDT devices is critical for small-scale producers and field operators. Advances in miniaturization, wireless communication, and low-cost sensors should be prioritized to democratize access to sophisticated quality assessment tools, enabling on-site decision-making and reducing dependency on centralized laboratories.

3.15.5. Multi-sensor data fusion approaches

Combining data from multiple sensors and modalities through data fusion techniques can enhance the accuracy and comprehensiveness of quality assessments. Future research should focus on developing robust algorithms capable of integrating heterogeneous data sources, such as spectral, visual, and acoustic data, to provide holistic evaluations of olive product quality and safety.

3.15.6. Policy and industry adoption strategies

For successful translation into industry practice, stakeholders must collaborate to develop supportive policies, incentives, and regulatory frameworks that promote the adoption of advanced NDT methods. Training programs, demonstration projects, and pilot studies can facilitate industry acceptance, while addressing challenges related to cost, scalability, and user expertise. In conclusion, harnessing emerging technologies, fostering standardization, and promoting industry integration are essential steps toward realizing the full potential of nondestructive techniques powered by AI and big data analytics in ensuring the quality and safety of olive products. Strategic investments and collaborative efforts will be crucial to shape a sustainable and innovative future in this domain.

4. Novelty impact statement and significance of the study

This systematic review provides a comprehensive synthesis of the latest technological innovations at the intersection of nondestructive testing, AI, and big data analytics tailored specifically for olive product assessment. The study highlights how these integrated approaches can revolutionize quality control processes, reduce reliance on destructive testing, and enable real-time, high-throughput analysis. Its significance lies in identifying research gaps, promoting interdisciplinary collaboration, and guiding industry stakeholders toward adopting smarter, more sustainable quality assurance systems. Ultimately, this review underscores the transformative potential of intelligent nondestructive techniques to enhance product safety, authenticity, and consumer confidence in the olive industry.

5. Alignment of Study with the United Nations' Sustainable Development Goals (SDGs)

This study strongly supports SDG 2 (Zero Hunger) by advancing innovative, sustainable, and efficient methods for assessing the quality and safety of olive products, which are vital for global food security. By integrating nondestructive techniques with AI and big data analytics, the research promotes the development of rapid, reliable, and cost-effective quality assurance systems that can be deployed across the entire supply chain. These advancements help reduce food loss and waste by enabling early detection of spoilage, contamination, and adulteration, thereby ensuring that safe and nutritious olive products reach consumers. Furthermore, the emphasis on sustainable and scalable technologies aligns with the goal of improving agricultural productivity and resilience, ultimately contributing to the availability of healthy food options and supporting the fight against hunger worldwide. Moreover, the study aligns with several United Nations Sustainable Development Goals, particularly SDG 3 (Good Health and Well-being), by promoting safer and higher-quality olive products that contribute to consumer health. It also supports SDG 12 (Responsible Consumption and Production) by encouraging sustainable and efficient quality assessment practices that reduce waste and resource use. Furthermore, the research advances SDG 9 (Industry, Innovation, and Infrastructure) by fostering technological innovation and capacity-building within the food industry. By promoting sustainable, efficient, and science-based approaches to food safety and quality, this study contributes to the global agenda of ensuring healthy diets, reducing environmental impact, and fostering resilient agricultural systems.

4. Conclusion

The integration of NDT with AI and BDA offers a promising frontier for the enhanced quality and safety assessment of olive products. These approaches provide rapid, accurate, and cost-effective solutions that surpass traditional methods, supporting producers in ensuring product integrity and consumer safety. Computational pharmacology contributes to understanding complex chemical interactions and bioactive compound behavior in olive products, enhancing safety and quality assessments. Challenges include data heterogeneity, lack of standardization, high instrumentation costs, interpretability of AI models, and regulatory hurdles. Future research should focus on developing unified frameworks, expanding datasets, and fostering industry adoption to fully realize the potential of these innovative technologies. Ultimately, the continued advancement and integration of AI-driven NDT hold the potential to transform quality management practices within the olive industry, ensuring higher standards and consumer trust.

Abbreviations

ADMET: Absorption, Distribution, Metabolism, Excretion, and Toxicity
AI: artificial intelligence
ANN: artificial neural network
BDA: big data analytics
CNN: convolutional neural network
CT: computed tomography
DL: deep learning
EU: European Union
EVOO: extra virgin olive oil
FTIR: Fourier Transform Infrared
HSI: hyperspectral imaging
IoT: Internet of Things
MD: molecular dynamics
MRI: magnetic resonance imaging
ML: machine learning
NDT: nondestructive techniques
NIR: near-infrared
NLP: natural language processing
PRISMA: Preferred Reporting Items for Systematic reviews and Meta-Analyses

QSAR: quantitative structure-activity relationship

RF: random forest

RNNs: Recurrent Neural Networks

SC: supply chain

SDGs: Sustainable Development Goals

SVM: support vector machines

TRL: Technology Readiness Level

UN: United Nations

XRF: X-Ray Fluorescence

Acknowledgements

Not applicable.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability

The authors confirm that the data supporting the findings of this study are available within the article.

Clinical trial number

Not applicable.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

5. References

1. Jimenez-Lopez C, Carpena M, Lourenço-Lopes C, Gallardo-Gomez M, Lorenzo JM, Barba FJ, Prieto MA, Simal-Gandara J. Bioactive Compounds and Quality of Extra Virgin Olive Oil. *Foods*. 2020; 9(8):1014. https://doi.org/10.3390/foods9081014
2. Nikou, Theodora et al. “Olive Oil Quality and Authenticity Assessment Aspects Employing FIA-MRMS and LC-Orbitrap MS Metabolomic Approaches.” *Frontiers in public health.* vol. 8 558226. 25 Sep. 2020, https://doi.org/10.3389/fpubh.2020.558226

3. María-del-Mar Garrido-Cuevas, Ana-María Garrido-Varo, María-Teresa Sánchez, Dolores Pérez-Marín. A novel approach to olive oil sensory profiling: Predicting key attributes using near-infrared spectroscopy and open-source software. *Food Control*. vol. 181, 2026, 111726, https://doi.org/10.1016/j.foodcont.2025.111726
4. Ramesh, T. & Erkinbaev, C. Integrating advanced imaging techniques with Industry 4.0 technologies for real-time quality monitoring in the agri-food sector: A review. *Digital Chemical Engineering*. vol. 19, 2026, 100301, https://doi.org/10.1016/j.dche.2026.100301
5. Kazou, M., Psarafti, K. & Panagou, E.Z. The future of the table olive sector: unlocking the potential of process analytical technology (PAT) in the era of digital transformation. *Eur Food Res Technol* 251, 3489–3504 (2025). https://doi.org/10.1007/s00217-025-04892-x
6. Noguera M, Millan B, Aquino A, Andújar JM. Methodology for Olive Fruit Quality Assessment by Means of a Low-Cost Multispectral Device. *Agronomy*. 2022; 12(5):979. https://doi.org/10.3390/agronomy12050979
7. Gbashi S, Njobeh PB. Enhancing Food Integrity through Artificial Intelligence and Machine Learning: A Comprehensive Review. *Applied Sciences*. 2024; 14(8):3421. https://doi.org/10.3390/app14083421
8. Parlak, İ.H., Milli, M. & Milli, N.S. Machine Learning–Based Detection of Olive Oil Adulteration Using BME688 Gas Sensor Matrix. *Food Anal. Methods* 18, 1454–1464 (2025). https://doi.org/10.1007/s12161-025-02803-0
9. Gopal, P.R.C., Rana, N.P., Krishna, T.V. *et al.* Impact of big data analytics on supply chain performance: an analysis of influencing factors. *Ann Oper Res* 333, 769–797 (2024). https://doi.org/10.1007/s10479-022-04749-6
10. Parra-López, C., Ben Abdallah, S., Hassoun, A., Jagtap, S., Garcia-Garcia, G., Ben Hassen, T. et al. Digital and Industry 4.0 technologies in olive farming and industry: Recent applications and future outlook. *Smart Agricultural Technology*. vol. 12, 2025, 101376, https://doi.org/10.1016/j.atech.2025.101376
11. Mehany T, González-Sáiz JM, Pizarro C. The Quality Prediction of Olive and Sunflower Oils Using NIR Spectroscopy and Chemometrics: A Sustainable Approach. *Foods*. 2025; 14(13):2152. https://doi.org/10.3390/foods14132152
12. Adade, S.Y-S.S., Lin, H., Johnson, N.A.N., Nunekpeku, X., John-Nelson Ekumah, J-N., Kwadzokpui, B.A. et al. Spectroscopic techniques for edible oil evaluation - Technology overview and recent applications from lab to industry. *Food Control*, vol 176, 2025, 111352. https://doi.org/10.1016/j.foodcont.2025.111352

13. Prempeh, N.Y.A., Nunekpeku, X., Kutsanedzie, F.Y.H., Murugesan, A., Li, H.A. Comprehensive Review of Non-Destructive Monitoring of Food Freshness and Safety Using NIR Spectroscopy and Biosensors: Challenges and Opportunities. *Chemosensors*. 2025; 13(11):393. https://doi.org/10.3390/chemosensors13110393
14. Almoselhy, R.I.M., Allam, M.H., El-Kalyoubi, M.H., El-Sharkawy, A.A. ^{1}H NMR spectral analysis as a new aspect to evaluate the stability of some edible oils. *Annals of Agricultural Sciences*, vol. 59, 2, 2014, Pages 201-206, https://doi.org/10.1016/j.aoas.2014.11.006
15. Tejedor, B., Lucchi, E., Bienvenido-Huertas, Nardi, D.I. Non-destructive techniques (NDT) for the diagnosis of heritage buildings: Traditional procedures and futures perspectives. *Energy and Buildings*, vol. 263, 2022, 112029, https://doi.org/10.1016/j.enbuild.2022.112029
16. Pan, M. Nondestructive Testing in Food Quality and Safety: Development and Applications. *Foods*. 2025; 14(13):2339. https://doi.org/10.3390/foods14132339
17. Shetu, M.S.A. (2024). A Review of Nondestructive Testing Methods for Aerospace Composite Materials. *Journal of Computers, Mechanical and Management*, 3(1), 30–41. https://doi.org/10.57159/gadl.jcmm.3.1.240117
18. Abdollahi-Mamoudan, F., Ibarra-Castanedo, C., Maldague, X.P.V. Non-Destructive Testing and Evaluation of Hybrid and Advanced Structures: A Comprehensive Review of Methods, Applications, and Emerging Trends. *Sensors*. 2025; 25(12):3635. https://doi.org/10.3390/s25123635
19. Silva, M.I., Malitckii, E., Santos, T.G., Vilaça, P. Review of conventional and advanced non-destructive testing techniques for detection and characterization of small-scale defects. *Progress in Materials Science*, vol. 138, 2023, 101155, https://doi.org/10.1016/j.pmatsci.2023.101155
20. Zhang, Y., Chow, C.L., Lau, D. Artificial intelligence-enhanced non-destructive defect detection for civil infrastructure. *Automation in Construction*, vol. 171, 2025, 105996, https://doi.org/10.1016/j.autcon.2025.105996
21. Leopardi, L., Mangeruga, V., Giacopini, M., Di Settimi, M., Rosi, R. Development of a Test Rig for Detecting Fatigue Cracks in a Plastic Component of a Medical Device via Acoustic Signal Acquisitions. *Machines*. 2025; 13(12):1118. https://doi.org/10.3390/machines13121118
22. Nahar, L., Awrangjeb, M., Islam, M.S. AI-enabled defect detection in industrial products: A comprehensive survey, key insights and future research challenges.

Advanced Engineering Informatics, vol. 69, Part D, 2026, 104067, https://doi.org/10.1016/j.aei.2025.104067

23. Ghattas, A., Al-Sharawi, R., Zakaria, A., Qaddoumi, N. Detecting Defects in Materials Using Nondestructive Microwave Testing Techniques: A Comprehensive Review. *Applied Sciences*. 2025; 15(6):3274. https://doi.org/10.3390/app15063274
24. Li, M., Yin, H., Gu, F., Duan, Y., Zhuang, W., Han, K. et al. Recent Advances and Applications of Nondestructive Testing in Agricultural Products: A Review. *Processes*. 2025; 13(9):2674. https://doi.org/10.3390/pr13092674
25. Amraei, J, Katunin, A., Dragan, K., Colombo, C., Świderski, W., Salerno, A. et al. Quantification and fusion of thermography and ultrasonic non-destructive testing results for composites with low-velocity impact damage. *Composites Part B: Engineering*, vol. 312, 2026, 113293, https://doi.org/10.1016/j.compositesb.2025.113293
26. Shaloo M, Schnall M, Klein T, Huber N, Reitinger B. A Review of Non-Destructive Testing (NDT) Techniques for Defect Detection: Application to Fusion Welding and Future Wire Arc Additive Manufacturing Processes. *Materials*. 2022; 15(10):3697. https://doi.org/10.3390/ma15103697
27. Sinelli, N., Cerretani, L., Di Egidio, V., Bendini, A., Casiraghi, E. Application of near (NIR) infrared and mid (MIR) infrared spectroscopy as a rapid tool to classify extra virgin olive oil on the basis of fruity attribute intensity. *Food Research International*, vol. 43, 1, 2010, 369-375, https://doi.org/10.1016/j.foodres.2009.10.008
28. Mehany, T., González-Sáiz, J.M., Pizarro, C. Quantification of Phenolic Compounds in Olive Oils by Near-Infrared Spectroscopy and Multiple Regression: Effects of Cultivar, Hydroxytyrosol Supplementation, and Deep-Frying. *Antioxidants* (Basel). 2025 May 31;14(6):672. https://doi.org/10.3390/antiox14060672
29. Arroyo-Cerezo, A., Yang, X., Jiménez-Carvelo, A.M., Pellegrino, M., Savino, A.F., Berzaghi, P. Assessment of extra virgin olive oil quality by miniaturized near infrared instruments in a rapid and non-destructive procedure. *Food Chemistry*, vol. 430, 2024, 137043, https://doi.org/10.1016/j.foodchem.2023.137043
30. Ding F, Sánchez-Villasclaras S, Pan L, Lan W, García-Martín JF. Advances in Vibrational Spectroscopic Techniques for the Detection of Bio-Active Compounds in Virgin Olive Oils: A Comprehensive Review. *Foods*. 2024; 13(23):3894. https://doi.org/10.3390/foods13233894
31. Medina–García, M., Amigo, J.M., Martínez-Domingo, M.A., Valero, E.M., Jiménez–Carvelo, A.M. Strategies for analysing hyperspectral imaging data for food quality

and safety issues – A critical review of the last 5 years. *Microchemical Journal*, vol. 214, 2025, 113994, https://doi.org/10.1016/j.microc.2025.113994

32. Wu, S., Huang, L., Huang, R. Review of advances in hyper-spectral imaging-based non-destructive testing methods in food application. *Journal of Food Composition and Analysis*, vol. 150, 2026, 108860, https://doi.org/10.1016/j.jfca.2026.108860
33. Aboalhaija, N., Harfouche, M., Khalil, E., Abaza, I., Afifi, F. Elemental Analysis of Olives' Fruits Using Synchrotron Radiation X-Ray Fluorescence (XRF). *Jordan Journal of Pharmaceutical Sciences*, vol. 18, no. 4, Dec. 2025, pp. 970-7, https://doi.org/10.35516/jjps.v18i4.3099
34. Comino, F., Ayora-Cañada, M.J., Aranda, V., Díaz, A., Domínguez-Vidal, A. Near-infrared spectroscopy and X-ray fluorescence data fusion for olive leaf analysis and crop nutritional status determination. *Talanta*, vol. 188, 2018, Pages 676-684, https://doi.org/10.1016/j.talanta.2018.06.058
35. Alouache, B., Khechena, F.K., Lecheb, F., Boutkedjirt, T. Characterization of Olive Oil by Ultrasonic and Physico-chemical Methods. *Physics Procedia*, vol. 70, 2015, Pages 1061-1065, https://doi.org/10.1016/j.phpro.2015.08.226
36. Zarezadeh, M.R., Aboonajmi, M., Ghasemi-Varnamkhasti, M. Applications of ultrasound techniques in tandem with non-destructive approaches for the quality evaluation of edible oils. *J Food Sci Technol.* 2022 Aug;59(8):2940-2950. https://doi.org/10.1007/s13197-022-05351-1
37. Jiménez, A., Rufo, M., Paniagua, J.M., González-Mohino, A., Olegario, L.S.. Temperature dependence of acoustic parameters in pure and blended edible oils: Implications for characterization and authentication. *Ultrasonics*, vol. 138, 2024, 107216, https://doi.org/10.1016/j.ultras.2023.107216
38. Wang X, Lei Q, Luo J, Ye Y, Wu X, Xiao P, Liu Y. Visualization Study of Produced Oil Based on Magnetic Resonance Imaging Technology. *ACS Omega*. 2021 Jan 15;6(4):3244-3251. https://doi.org/10.1021/acsomega.0c05702
39. Anjali, Jena, A., Bamola, A. et al. State-of-the-art non-destructive approaches for maturity index determination in fruits and vegetables: principles, applications, and future directions. *Food Prod Process and Nutr* 6, 56 (2024). https://doi.org/10.1186/s43014-023-00205-5
40. Vanaraj, R., I.P, B., Mayakrishnan, G., Kim I.S., Kim. S-C. A Systematic Review of the Applications of Electronic Nose and Electronic Tongue in Food Quality Assessment and Safety. *Chemosensors*. 2025; 13(5):161. https://doi.org/10.3390/chemosensors13050161

41. Feng, J., Zheng, F., Zhang, Y., Zeng, X., Wang, Z., Liang, J. et al. Exploring the broad spectrum of machine learning technologies in the food sector: A comprehensive review of techniques and practical applications. *Curr Res Food Sci.* 2026 Apr 8;12:101406. https://doi.org/10.1016/j.crfs.2026.101406
42. Fu, Y., Sun, DW. Advancing Fruit Quality Monitoring with Artificial Intelligence-Augmented Non-Destructive Technologies. *Food Eng Rev* 18, 9 (2026). https://doi.org/10.1007/s12393-026-09437-w
43. Ziani, I., Bouakline, H., El Guerraf, A., El Bachiri, A., Fauconnier, M-L. Sher, F.. Integrating AI and advanced spectroscopic techniques for precision food safety and quality control. *Trends in Food Science & Technology*, vol. 156, 2025, 104850, https://doi.org/10.1016/j.tifs.2024.104850
44. Rayen, S.J., Jayabal, R., Singh, P. K. Pamuluri, V.K.N., Kannan, S., Ayyar, M. et al. Artificial Intelligence-Enabled Analytical Technologies for Chemical Engineering. *Chemical Engineering & Technology*, 49, no. 4 (2026): e70213. https://doi.org/10.1002/ceat.70213
45. Daihao, S., Min, W., Yanjun, L., Lei, X., Zhichao, L. Research progress of non-destructive testing techniques in moisture content determination. *Smart Agricultural Technology*, vol. 11, 2025, 100878, https://doi.org/10.1016/j.atech.2025.100878
46. Tai, J.L., Sultan, M.T.H., Łukaszewicz, A., Józwik, J., Oksiuta, Z., Shahar, F.S. Recent Trends in Non-Destructive Testing Approaches for Composite Materials: A Review of Successful Implementations. *Materials* (Basel). 2025 Jul 2;18(13):3146. https://doi.org/10.3390/ma18133146
47. Plyduang, T., Monton, C., Suksaeree, J. Sustainable green extraction approaches for herbal phytochemicals supporting environmentally friendly and climate responsive product development. *Sustainable Chemistry for Climate Action*, vol. 8, 2026, 100184, https://doi.org/10.1016/j.scca.2026.100184
48. Hussein, J.B., Workneh, T.S., Kassim, A., Ntsowe, K., Melesse, S.F., El-Mesery, H.S. A review on the impact of big data analytics in transforming agricultural practices, food processing, and preservation strategies. *Applied Food Research*, vol. 5, 2, 2025, 101234, https://doi.org/10.1016/j.afres.2025.101234
49. Rossi, S., Gemma, S., Borghini, F., Perini, M., Butini, S., Carullo, G. et al. Agri-food traceability today: Advancing innovation towards efficiency, sustainability, ethical sourcing, and safety in food supply chains. *Trends in Food Science & Technology*, vol. 163, 2025, 105154, https://doi.org/10.1016/j.tifs.2025.105154

50. Bhat, M.A., Rather, M.Y., Singh, P., Hassan, S., Hussain, N. Advances in smart food authentication for enhanced safety and quality. *Trends in Food Science & Technology*, vol. 155, 2025, 104800, https://doi.org/10.1016/j.tifs.2024.104800
51. Liakos, K.G., Athanasiadis, V., Bozinou, E., Lalas, S.I. Machine Learning for Quality Control in the Food Industry: A Review. *Foods*. 2025; 14(19):3424. https://doi.org/10.3390/foods14193424
52. Leone, A., Berardi, A., Antonelli, G., Dellisanti, C.D., Tamborrino, A. NIR Spectroscopy for the Online Monitoring of Water and Olive Oil Content in Pomace during the Extraction Process. *Applied System Innovation*. 2024; 7(5):96. https://doi.org/10.3390/asi7050096
53. Almoselhy, R.I.M. Application of some Methods for Detecting Adulteration in Olive Oil [M.Sc. Dissertation]. Ain Shams University, Faculty of Agriculture, Department of Food Science, 2010. https://doi.org/10.2139/ssrn.3908539
54. Almoselhy, R.I.M. New Aspects on Stability of some Edible Oils [Ph.D. Dissertation]. Ain Shams University, Faculty of Agriculture, Department of Food Science, 2015. https://doi.org/10.2139/ssrn.3908543
55. Hashem, H., Almoselhy, R.I.M., El-Waseif, M., Magdy, A. Rapid Authentication of Extra Virgin Olive Oil using UV and FTIR Spectroscopy. *Middle East J Appl Sci*. 2020;10(2):263-71. https://doi.org/10.36632/mejas/2020.10.2.25
56. Usmani, A., Almoselhy, R.I.M. Novel positioning of *Olea europaea* L. (Olive) from farm to pharma indexed in pharmacopeia. *J Nutr Metab Health Sci*, vol. 6, no. 4, 2023, pp. 161-170. https://doi.org/10.18231/j.ijnmhs.2023.027
57. Almoselhy, R.I.M. A Comprehensive Review of Characterization and Detection of Adulteration of Extra Virgin Olive Oil. *Am Res J Agricul*. 2020;6(1):1-8. https://doi.org/10.21694/2378-9018.20003
58. Domínguez-Cid, S., Larios, D.F., Barbancho, J., Molina, F.J., Guerra, J.A., León, C. Identification of Olives Using In-Field Hyperspectral Imaging with Lightweight Models. *Sensors*. 2024; 24(5):1370. https://doi.org/10.3390/s24051370
59. Li, X., Wang, D., Yu, L., Ma, F., Wang, X., Zhang, L. et al. Multiple adulteration detection of olive oils by Raman spectroscopy, *Oil Crop Science*, vol. 10, 4, 2025, Pages 348-353. https://doi.org/10.1016/j.ocsci.2025.08.001
60. Zarezadeh, M.R., Aboonajmi, M., Varnamkhasti, M.G. Fraud detection and quality assessment of olive oil using ultrasound. *Food Sci Nutr*.2021;9:180–189. https://doi.org/10.1002/fsn3.1980

61. Zarezadeh, M.R., Aboonajmi, M., Varnamkhasti, M.G., Azarikia, F. Olive Oil Classification and Fraud Detection Using E-Nose and Ultrasonic System. *Food Anal. Methods* 14, 2199–2210 (2021). https://doi.org/10.1007/s12161-021-02035-y
62. Cappelli, A., Cividino, S., Redaelli, V., Tripodi, G., Aiello, G., Velotto, S. et al. Applying Spectroscopies, Imaging Analyses, and Other Non-Destructive Techniques to Olives and Extra Virgin Olive Oil: A Systematic Review of Current Knowledge and Future Applications. *Agriculture*. 2024; 14(7):1160. https://doi.org/10.3390/agriculture14071160
63. Borisjuk, L., Neuberger, T., Rolletschek, H. Lipid MRI in plant science: principles and potential areas of application, *Journal of Experimental Botany*, 2025; eraf479. https://doi.org/10.1093/jxb/eraf479
64. Alkanan, Z.T., Altemimi, A.B., Awlqadr, F.H., Alkaisy, Q.H., Hashemi, S.M.B., Pratap-Singh, A. Exploring the Frontiers of Food Science: A Comprehensive Review of Advanced Magnetic Resonance Applications in Food Analysis, Quality Analysis, and Safety Assessment. *Food Sci Nutr*.2025:13, no. 7: e70643. https://doi.org/10.1002/fsn3.70643
65. Aqeel, M., Sohaib, A., Iqbal, M., Rehman, H.U., Rustam, F. Hyperspectral identification of oil adulteration using machine learning techniques. *Curr Res Food Sci*. 2024 May 22;8:100773. https://doi.org/10.1016/j.crfs.2024.100773
66. Lee, J-E., Kim, M-J., Lee, B-Y., Hwan, L.J., Yang, H-E., Kim, M.S. et al. Evaluating ripeness in post-harvest stored kiwifruit using VIS-NIR hyperspectral imaging. *Postharvest Biology and Technology*, vol. 225, 2025, 113496, https://doi.org/10.1016/j.postharvbio.2025.113496
67. Thuku, J.M., Kaniu, M.I., Ndung'u, C.N., Kiruri, L.W., Kaduki, K.A. Rapid trace detection of chlorpyrifos in vegetables using 2D Raman correlation spectroscopy and machine learning. *LWT*, vol. 237, 2025, 118742, https://doi.org/10.1016/j.lwt.2025.118742
68. Tang, T., Zhang, M., Jia, H., Adhikari, B., Guo, Z. Real-time freshness monitoring of fruits and vegetables integrating 3D-printed alginate-based colorimetric sensors with deep convolutional neural networks, *Chemical Engineering Journal*, vol. 520, 2025, 166387, https://doi.org/10.1016/j.cej.2025.166387
69. Abdollahi-Mamoudan, F., Ibarra-Castanedo, C., Maldague, X.P.V. Non-Destructive Testing and Evaluation of Hybrid and Advanced Structures: A Comprehensive Review of Methods, Applications, and Emerging Trends. *Sensors*. 2025; 25(12):3635. https://doi.org/10.3390/s25123635

70. Kheiralipour, K., Sajadipour, F., Nadimi, M. A review of nut quality assessment using hyperspectral imaging technique. *Journal of Food Composition and Analysis*, vol. 148, Part 1, 2025, 108184, https://doi.org/10.1016/j.jfca.2025.108184
71. Malavi, D., Raes, K., Van Haute, S. Integrating near-infrared hyperspectral imaging with machine learning and feature selection: Detecting adulteration of extra-virgin olive oil with lower-grade olive oils and hazelnut oil. *Curr Res Food Sci.* 2024 Oct 29;9:100913. https://doi.org/10.1016/j.crfs.2024.100913
72. Guerri, M.F., Distante, C., Spagnolo, P., Bougourzi, F., Taleb-Ahmed, A. Deep learning techniques for hyperspectral image analysis in agriculture: A review. *ISPRS Open Journal of Photogrammetry and Remote Sensing*, vol. 12, 2024, 100062, https://doi.org/10.1016/j.ophoto.2024.100062
73. Chen, Z., Zhang, G., Zhang, F. Multimodal AI for Real-Time Food Safety and Quality: From Sensors to Foundation Models, Edge Deployment, and Regulation. *Food Sci Nutr.*2026:14, no. 2: e71534. https://doi.org/10.1002/fsn3.71534
74. Yfanti, S., Sakkas, N. Technology Readiness Levels (TRLs) in the Era of Co-Creation. *Applied System Innovation*. 2024; 7(2):32. https://doi.org/10.3390/asi7020032
75. Gariya, N., Libber, M., Singh, N. THz Spectroscopy - A Non-Invasive Technique for Quality Assessment of Agricultural Products. *Food Control*, 2026, 112247, https://doi.org/10.1016/j.foodcont.2026.112247
76. Pu, Y., Pérez-Marín, D., O'Shea, N., Garrido-Varo, A. Recent Advances in Portable and Handheld NIR Spectrometers and Applications in Milk, Cheese and Dairy Powders. *Foods*. 2021 Oct 8;10(10):2377. https://doi.org/10.3390/foods10102377
77. Martínez-García, J.M., Hernán, J., Vanderlinden, K., Laguna, A.M., Giráldez, J.V., Martinez, G. IoT-based monitoring and management system for effluents reuse from table olive processing facilities in olive groves: Toward circular water management. *Water Resources and Industry*, vol. 35, 2026, 100357, https://doi.org/10.1016/j.wri.2026.100357
78. Zarezadeh, M.R., Aboonajmi, M., Ghasemi-Varnamkhasti, M. The effect of data fusion on improving the accuracy of olive oil quality measurement. *Food Chemistry: X*, vol. 18, 2023, 100622, https://doi.org/10.1016/j.fochx.2023.100622
79. Almoselhy, R.I.M., Usmani, A., Rajendran, R., Thomas, S. (2026). AI and Big Data Analytics for Management of Nutraceuticals. In: Rajendran, R., Thomas, S. (eds) Handbook of Nutraceuticals. Springer, Cham. https://doi.org/10.1007/978-3-031-98791-5_50

80. Almoselhy, R.I.M., Usmani, A. (2024). AI in Food Science: Exploring Core Elements, Challenges, and Future Directions. Open Access Journal of Microbiology & Biotechnology, 9(4): 000313, 1-15. https://doi.org/10.23880/oajmb-16000313
81. Ding, H., Tian, J., Yu, W., Wilson, D.I., Young, B.R., Cui, X., et al. The Application of Artificial Intelligence and Big Data in the Food Industry. *Foods*. 2023; 12(24):4511. https://doi.org/10.3390/foods12244511
82. Ghavidelan, M.A., Sahari, M.A., Banakar, A., Minaei, S., Zarein, M. Detection of adulteration in pure olive oil using the UV-Vis spectroscopy coupled with machine learning. *Applied Food Research*, 6, 1, 2026, 101763, https://doi.org/10.1016/j.afres.2026.101763
83. Lonetti, F., Martelli, F., Resta, G. Artificial neural networks applied to olive oil production and characterization: A systematic review. *Intelligent Systems with Applications*, vol. 26, 2025, 200525, https://doi.org/10.1016/j.iswa.2025.200525
84. Meoni, G., Tenori, L., Di Cesare, F., Brizzolara, S., Tonutti, P., Cherubini, C. et al. NMR-based metabolomic approach to estimate chemical and sensorial profiles of olive oil. *Comput Struct Biotechnol J.* 2025;27:1359-1369. https://doi.org/10.1016/j.csbj.2025.03.045
85. Mendes, J., Lima, J., Costa, L., Rodrigues, N., Pereira, A.I. Deep learning networks for olive cultivar identification: A comprehensive analysis of convolutional neural networks. *Smart Agricultural Technology*, vol. 8, 2024, 100470, https://doi.org/10.1016/j.atech.2024.100470
86. Sayago, A., González-Domínguez, R., Beltrán, R., Fernández-Recamales, Á. Combination of complementary data mining methods for geographical characterization of extra virgin olive oils based on mineral composition. *Food Chemistry*, vol. 261, 2018, Pages 42-50, https://doi.org/10.1016/j.foodchem.2018.04.019
87. Blazakis, K.N., Stupichev, D., Kosma, M., El Chami, M.A.H., Apodiakou, A., Kostelenos, G. et al. Discrimination of 14 olive cultivars using morphological analysis and machine learning algorithms. *Front. Plant Sci.* (2024);15:1441737. https://doi.org/10.3389/fpls.2024.1441737
88. Osco-Mamani, E., Santana-Carbajal, O., Chaparro-Cruz, I., Ochoa-Donoso, D., Alcazar-Alay, S. The Detection and Counting of Olive Tree Fruits Using Deep Learning Models in Tacna, Perú. *AI*. 2025; 6(2):25. https://doi.org/10.3390/ai6020025
89. Parra-López, C., Ben Abdallah, S., Hassoun, A., Jagtap, S., Garcia-Garcia, G., Ben Hassen, T. et al. Digital and Industry 4.0 technologies in olive farming and industry:

Recent applications and future outlook. *Smart Agricultural Technology*, vol. 12, 2025, 101376, https://doi.org/10.1016/j.atech.2025.101376

90. Ferrari, C., Foca, G., Ulrici, A. Handling large datasets of hyperspectral images: reducing data size without loss of useful information. *Anal Chim Acta*. 2013 Nov 13;802:29-39. https://doi.org/10.1016/j.aca.2013.10.009
91. Domínguez-Cid, S., Larios, D.F., Barbancho, J., Molina, F.J., Guerra, J.A., León, C. Identification of Olives Using In-Field Hyperspectral Imaging with Lightweight Models. *Sensors*. 2024; 24(5):1370. https://doi.org/10.3390/s24051370
92. Garrido-Romero, M., Díez-Municio, M., Moreno, F.J. Global Status, Recent Trends, and Knowledge Mapping of Olive Bioactivity Research Through Bibliometric Analysis (2000-2024). *Foods*. 2025 Apr 14;14(8):1349. https://doi.org/10.3390/foods14081349
93. Unsal, V., Yıldız, R., Korkmaz, A., Mert, B.D., Calıskan, C.G., Oner, E. Evaluation of extra virgin olive oil compounds using computational methods: in vitro, ADMET, DFT, molecular docking and human gene network analysis study. *BMC Chem.* 2025 Jan 3;19(1):3. https://doi.org/10.1186/s13065-024-01369-y
94. Mohamaden, Y.M., El-Hawary, S.S., El-Fakharany, E.M., El-Maradny, Y.A., El Raey,, M., El Senousy, A.S. et al. Network pharmacology of olive stem extract, UPLC-HR-QTOF-MS profiling and antiviral activities aligned with UN sustainable development goals. *Sci Rep* 15, 23665 (2025). https://doi.org/10.1038/s41598-025-07452-1
95. Cuyàs, E., Castillo, D., Llorach-Parés, L., Lozano-Sánchez, J., Verdura, S., Nonell-Canals, A. et al. Computational de-orphanization of the olive oil biophenol oleacein: Discovery of new metabolic and epigenetic targets. *Food and Chemical Toxicology*, vol. 131, 2019, 110529, https://doi.org/10.1016/j.fct.2019.05.037
96. Gentile, L., Uccella, N.A., Sivakumar, G. Soft-MS and Computational Mapping of Oleuropein. *International Journal of Molecular Sciences.* 2017; 18(5):992. https://doi.org/10.3390/ijms18050992
97. Fatoki, T.H., Akintayo, C.O., Ibraheem, O. Bioinformatics exploration of olive oil: molecular targets and properties of major bioactive constituents. *OCL*, 28 (2021) 36. https://doi.org/10.1051/ocl/2021024
98. Bourdakou, M.M., Melliou, E., Magiatis, P., Spyrou, G.M. Computational investigation of the functional landscape of the protective role that extra virgin olive oil consumption may have on chronic lymphocytic leukemia. *J Transl Med* 22, 869 (2024). https://doi.org/10.1186/s12967-024-05672-z

99. Bilal, R.M., Liu, C., Zhao, H., Wang, Y., Farag, M.R., Alagawany, M. et al. Olive Oil: Nutritional Applications, Beneficial Health Aspects and its Prospective Application in Poultry Production. *Front. Pharmacol.* 2021;12:723040. https://doi.org/10.3389/fphar.2021.723040

100. Meoni, G., Vita, C., Tenori, L., Venturini, L., Ascolese, M., Mattei, A. et al. Machine learning supported olive oil compound profiling for assessing geographic and cultivar authenticity. *Food Research International*, vol. 233, Part 2, 2026, 118890, https://doi.org/10.1016/j.foodres.2026.118890

101. Boutalaka, M., Ouazzani, N., Stathopoulos, P., Xenaki, M., Maghat, H., Lakhlifi, T. et al. Exploring the Health Benefits of Phenolic Compounds in Moroccan Virgin Olive Oil: Chemical Profiling, Antioxidant Activity, and Computational Insights into COX Inhibition. *Mor. J. Chem.* May 2025, 13(3), 1038-1074. https://doi.org/10.48317/IMIST.PRSM/morjchem-v13i3.53562

102. Melo Ferreira, D., Oliveira, M.B.P.P., Alves, R.C. A Comprehensive Review of the Antitumor Activity of Olive Compounds: The Case of Olive Oil, Pomace, and Leaf Extracts, Phenolic Alcohols, Secoiridoids, and Triterpenes. *Antioxidants*. 2025; 14(2):237. https://doi.org/10.3390/antiox14020237

103. Mazri, R., Ouassaf, M., Zekri, A., Khan, S.U., Rengasamy, K.R.R., Alhatlani, B.Y. In Silico Network Pharmacology, Molecular Docking, and Molecular Dynamics Analysis of Rosemary-Derived Compounds as Potential HSP90 Inhibitors for Cancer Therapy. *Curr Issues Mol Biol.* 2025 Oct 18;47(10):860. https://doi.org/10.3390/cimb47100860

104. Thangavel, N., Al Bratty, M., Al Hazmi, H.A., Najmi, A., Ali Alaqi, R.O. Molecular Docking and Molecular Dynamics Aided Virtual Search of OliveNet™ Directory for Secoiridoids to Combat SARS-CoV-2 Infection and Associated Hyperinflammatory Responses. *Front Mol Biosci.* 2021 Jan 7;7:627767. https://doi.org/10.3389/fmolb.2020.627767

105. Ben Hassena, A., Abidi, J., Miled, N., Kulinowski, Ł., Skalicka-Woźniak, K., Bouaziz, M. New Insights into the Antibacterial Activity of Hydroxytyrosol Extracted from Olive Leaves: Molecular Docking Simulations of its Antibacterial Mechanisms. *Chem. Biodiversity*2025, 22, e202401714. https://doi.org/10.1002/cbdv.202401714

106. de la Torre, R., Carbó, M., Pujadas, M., Biel, S., Mesa, M-D., Covas, M-I. et al. Pharmacokinetics of maslinic and oleanolic acids from olive oil – Effects on endothelial function in healthy adults. A randomized, controlled, dose–response

study. *Food Chemistry*, vol. 322, 2020, 126676, https://doi.org/10.1016/j.foodchem.2020.126676

107. Subedi, P., Rodríguez, R.R., Thapa, P., Lantvit, D., Johnson, J.J. Pharmacokinetic Evaluation of Oleuropein from the Olive Tree (*Olea europaea*). *Nutraceuticals*. 2026; 6(2):24. https://doi.org/10.3390/nutraceuticals6020024

108. Korkmaz, A., Unsal, V., Yıldız, R. et al. Chemical evaluation of arbequina extra virgin olive oil with in silico analysis of its key phenolic compounds targeting LDL metabolism. *Sci Rep* 15, 33536 (2025). https://doi.org/10.1038/s41598-025-18144-1

109. Geromichalou, E.G., Geromichalos, G.D. In Silico Approach for the Evaluation of the Potential Antiviral Activity of Extra Virgin Olive Oil (EVOO) Bioactive Constituents Oleuropein and Oleocanthal on Spike Therapeutic Drug Target of SARS-CoV-2. *Molecules*. 2022; 27(21):7572. https://doi.org/10.3390/molecules27217572

110. Hua, Z., Zhang, X., Su, W., Zaky, A.A., Abd El-Aty, A.M., Xu, E. et al. Advancements in precision nutrition: Targeted strategies for personalized health. *The Innovation Life* 2026;4:100191. https://doi.org/10.59717/j.xinn-life.2026.100191

111. Huang, G., Khan, R., Zheng, Y., Lee, P.C., Li, Q., Khan, I. Exploring the role of gut microbiota in advancing personalized medicine. *Front Microbiol.* 2023 Nov 30;14:1274925. https://doi.org/10.3389/fmicb.2023.1274925

112. Singar, S., Nagpal, R., Arjmandi, B.H., Akhavan, N.S. Personalized Nutrition: Tailoring Dietary Recommendations through Genetic Insights. *Nutrients*. 2024; 16(16):2673. https://doi.org/10.3390/nu16162673

113. Rahimah, S., Tallei, T.E., Savitri, M., Yamada, C., Kim, H.J., Choi, M. et al. Functional foods and dietary matrices for metabolic improvement: an integrative review of mechanisms, evidence, and future directions. *Journal of Functional Foods*, vol. 139, 2026, 107240, https://doi.org/10.1016/j.jff.2026.107240

114. Alagiakrishnan, K., Halverson, T., Olivares, D.V.F., Sadowski, C.A. New Personalized Medicine Model for Medication Management. *Journal of Personalized Medicine*. 2026; 16(4):182. https://doi.org/10.3390/jpm16040182