



Food fermentations: NIR spectroscopy as a tool for process analytical technology

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Abstract

Fermentation is a cornerstone of the food system, offering several benefits in nutrition, food safety, sustainability, and sensory quality. Historically rooted in food preservation and cultural practices, fermentation has evolved into a dynamic biotechnological tool, spanning diverse applications from dairy, meat, vegetable, and plant-based foods to by-product valorization. The process leverages microbial metabolisms (primarily lactic acid bacteria, yeasts, and molds) to enhance shelf life and sensory properties, improve digestibility, and generate bioactive compounds. Advances in precision fermentation and strain engineering have further extended fermentation potential to address emerging food challenges. Traditional fermentation monitoring relies on manual, off-line techniques that lack real-time responsiveness. The integration of advanced sensor technologies, artificial intelligence (AI), and Process Analytical

Technology (PAT) enables real-time, non-invasive process control. Among these tools, near-infrared (NIR) spectroscopy stands out due to its speed, low cost, minimal sample preparation, and compatibility with multivariate data analysis. NIR spectroscopy, combined with machine learning models, has demonstrated robust performance in predicting fermentation parameters across multiple food matrices, including alcoholic beverages, dairy, plant and meat fermented products, bread, kombucha, and vinegar. However, challenges such as spectral complexity, calibration transferability, and model interpretability persist. Future perspectives emphasize the convergence of NIR spectroscopy with digital twins, hybrid modeling, and explainable AI, enabling self-optimizing, adaptive fermentation systems. Emerging NIR devices offer portability and scalability, democratizing access to smart fermentation control for both industrial and artisanal producers. This paradigm shift lays the groundwork for intelligent, sustainable, and precision-driven food fermentation.

Keywords Artificial intelligence; Alcoholic beverages; Dairy fermented products; Dry fermented sausages; Dough; Fermented plant materials; Machine learning; Process analytical technology; Vibrational spectroscopy; Vinegar



1. Introduction

Fermentation represents one of the oldest and most transformative technologies in human history. Its origins date back over 12,000 years, when it was used primarily for food preservation and enhancement of nutritional profile and digestibility. Early human societies practiced spontaneous fermentation of fruits, milk, and grains to ensure food availability during harsh seasons. Fermented beverages such as early forms of beer and wine were consumed in Neolithic communities, while dairy fermentation into yogurt or kefir likely developed in nomadic pastoralist societies. As societies evolved, so did fermentation practices, adapting to regional climates, available substrates, and microbial ecosystems. The importance of fermentation is underscored by its global presence; nearly every culture has its own traditional fermented foods, from kimchi in Korea and sauerkraut in Europe to injera in Ethiopia and natto in Japan. Nowadays, it is estimated that about a third of daily food consumption worldwide is made up of fermented foods, including fruits, vegetables, cereals, dairy products, fish, and meat (Ray et al., 2024).

Today, fermentation has become a cornerstone of industrial food biotechnology, driving innovations in probiotics, alternative proteins, functional foods, and waste valorization. Recent scientific breakthroughs in biotechnology, artificial intelligence (AI), and bioprocess engineering are unlocking new dimensions of fermentation that will likely shape the

future of food processing (Dissanayake et al., 2025; Kumar, Meghana, Pavani, Kumar, & Chintagunta, 2024).

Implementing effective monitoring and control systems is crucial to support expansion of fermentation processes, addressing issues such as culture growth variability, foam management, and biogenic amines formation. In particular, real-time measurement of pH, temperature, nutrient concentration, and microbial cells growth is paramount for ensuring immediate process adjustments and optimizations (Abbaspour, 2024). Control systems based on sensor technologies, data analytics, and communication protocols can effectively manage food safety risks and ensure the integrity and safety of the fermented foods (Abass, Eruaga, Itua, & Bature, 2024).

Tehrefore, this chapter, after outlining the relevance of fermentation processes in food production, will address both conventional and real-time approaches for process monitoring and control. Subsequently, it will highlight the effectiveness of near-infrared (NIR) spectroscopy combined with multivariate data analysis as a tool for Process Analytical Technology (PAT) applied to the food industry.



2. Fermentation in food processing

Fermentation is a metabolic process whereby microorganisms, including lactic acid bacteria (LAB), yeasts, and molds, convert organic substrates (mainly carbohydrates) into bioactive molecules such as lactic acid, ethanol, and carbon dioxide. These biochemical conversions occur in the absence of oxygen or under microaerophilic conditions, creating an environment inhospitable to many spoilage and pathogenic organisms. The transformation of simple or complex substrates into a variety of valuable compounds contributes significantly to the unique flavors, textures, and health benefits of fermented products (Izah, Odubo, Ogwu, & Hait, 2024).

LAB, notably species from the *Lactobacillus*, *Leuconostoc*, *Pediococcus*, and *Streptococcus* genera, dominate lactic fermentations. Their metabolic products, including organic acids and bacteriocins, lower the pH and inhibit undesirable microbes. LAB are particularly important in the fermentation of dairy products, vegetables, and cereals. Yeasts, such as *Saccharomyces cerevisiae*, are integral to alcoholic fermentations, converting sugars into ethanol and carbon dioxide, a process essential in

brewing, winemaking, and bread-leavening. Additionally, certain non-*Saccharomyces* yeasts contribute to aroma development and acid regulation. Molds, including *Penicillium*, *Rhizopus*, *Aspergillus*, and *Mucor* species, play crucial roles in fermenting soy-based foods (e.g., tempeh and miso) and in ripening cheeses, contributing to enzymatic degradation of proteins and fats that enhance flavor, aroma, and texture (Izah et al., 2024). These microorganisms may be used individually or synergistically in multi-microbial fermentations to achieve specific outcomes.

In modern food systems, fermentation is increasingly being exploited using starter cultures, i.e., carefully selected strains with predictable metabolic profiles. These cultures allow control over flavor, texture, safety, and fermentation kinetics, making them essential tools in standardized production environments. Moreover, advances in genomics and systems biology now enable the engineering of strains to enhance desired traits or introduce new functionalities, such as vitamin production, exopolysaccharide synthesis, or antimicrobial activity. The biological diversity and adaptability of fermentative microbes make fermentation one of the most versatile and robust tools for modern food innovation. It serves as a bridge between tradition and technology, enabling both the preservation of cultural food practices and the creation of novel, sustainable food solutions (Gänzle et al., 2024).

Fermentation versatility is evident in its applications spanning dairy, meat, vegetables, cereals, plant-based foods, and by-product valorization (Dissanayake et al., 2025; Olatunde et al., 2023). Fermented dairy products are among the most ancient and widely consumed fermented foods. Foods such as yogurt, kefir, sour cream, buttermilk, and various cheeses are produced through the activity of LAB and, in some cases, yeasts and molds. Most of the LAB that grow in dairy products can hydrolyze lactose, reducing its content, thus improving tolerance in lactose-intolerant individuals, although lactose is not always completely consumed. These microorganisms produce lactic acid, which lowers the pH and helps preserve the product. Acidification, exopolysaccharide production, and enzymatic reactions also contribute to the development of textural properties. Proteolytic activity during fermentation also leads to the release of bioactive peptides with potential antihypertensive, immunomodulatory, and antioxidant properties. In cheeses, molds such as *Penicillium roqueforti* and *Penicillium camemberti* are used to create the

distinct flavors and textures of blue and soft cheeses (Anumudu, Miri, & Onyeaka, 2024; Jang, Lee, & Paik, 2024).

In fermented meat and fish products, such as salami, pepperoni, sujuk, and fermented fish sauces, LAB and coagulase-negative staphylococci play central roles in acidification, flavor development, and pathogen control. These products undergo a curing and drying phase that, when coupled with microbial fermentation, imparts distinct aromas and textures while ensuring microbiological safety. Nitrite-reducing and color-stabilizing effects of the fermentative microbiota contribute to appealing sensory and visual qualities. The enzymatic breakdown of proteins and lipids generates flavor precursors, while controlled fermentation helps prevent spoilage and pathogenic growth (Izah et al., 2024; Stegmayer et al., 2023).

Fermentation of vegetables and fruits is common in many cultural contexts, with well-known examples including kimchi, sauerkraut, pickles, and brined olives. These products benefit from extended shelf life, increased vitamin content (notably vitamin C and B vitamins), and the presence of health-promoting probiotic bacteria. Spontaneous or inoculated LAB fermentations are often used, with strains such as *Lactobacillus plantarum* dominating. The metabolic activities of LAB reduce nitrate and pesticide residues, improve digestibility, and yield a complex array of aromatic compounds. Fruit-based fermentations also produce functional beverages, such as tepache and water kefir, which have probiotic and antioxidant properties (Aguirre-Garcia et al., 2024; Ray et al., 2024).

Cereal-based fermentations, such as in sourdough bread, involve the synergistic activity of yeasts and LAB. These microorganisms leaven the dough and contribute to the development of flavor, crust color, and texture. Importantly, fermentation reduces the glycemic index and improves mineral bioavailability by breaking down anti-nutritional compounds like phytic acid. In legumes, fermentation transforms raw soybeans into miso, tempeh, and natto, enhancing digestibility, increasing the concentration of bioavailable isoflavones, and producing bioactive substances such as natto kinase and gamma-polyglutamic acid. These products are notable for their high protein content and are integral components of traditional Asian diets (Abbaspour, 2024; Izah et al., 2024; Ray et al., 2024).

In response to consumer demand for sustainable and animal-free foods, fermentation plays a pivotal role in developing plant-based meat, dairy, and egg alternatives. It is used to improve the texture, flavor, and

nutritional quality of plant protein sources by reducing bitterness and increasing solubility. More recently, precision fermentation - a process involving genetically engineered microbes to produce target molecules - has enabled the creation of animal-identical proteins such as casein, whey, and egg albumin. These ingredients are now incorporated into vegan cheese, yogurt, and bakery products, where they replicate the sensory and functional properties of their animal-derived counterparts (Abbaspour, 2024; Alasi, Sanusi, Sunmonu, Odewole, & Adepoju, 2024).

Fermentation is a critical post-harvest step in the production of coffee and cocoa, where it serves to remove mucilage and initiate the biochemical changes responsible for developing flavor precursors. In coffee, yeast and bacterial populations drive mucilage degradation and initiate enzymatic conversions that shape acidity, body, and aroma. For cocoa, a succession of yeasts, LAB, and acetic acid bacteria facilitates the degradation of pulp and the development of chocolate flavor precursors through oxidative and enzymatic pathways. Controlled fermentation techniques are increasingly used to ensure consistency and elevate bean quality for specialty markets (Lopez-Palestino et al., 2025; Ray et al., 2024).

Fermentation also serves as a sustainable solution to valorize agro-industrial by-products. Dairy whey, fruit pomace, and vegetable peels, once considered waste, are now fermented to produce high-value products such as bioethanol, lactic acid, bioplastics, and functional beverages. These valorized streams reduce environmental impact and support the circular economy. Whey, for instance, can be fermented into probiotic drinks or used as a substrate for producing polyhydroxyalkanoates (PHAs), biodegradable plastics with growing relevance in food packaging. Similarly, citrus peels and grape pomace are fermented to extract antioxidants and develop natural preservatives (Areti et al., 2024; Kumar et al. 2023; Salas-Millán & Aguayo, 2024).

Together, these applications illustrate the profound and growing role of fermentation in shaping modern food systems, delivering enhanced nutrition, safety, flavor, and sustainability across a wide range of products.

2.1 Advantages of fermentation

Fermentation presents a suite of advantages that span health, food security, sustainability, product preservation, and sensory enrichment (Fig.

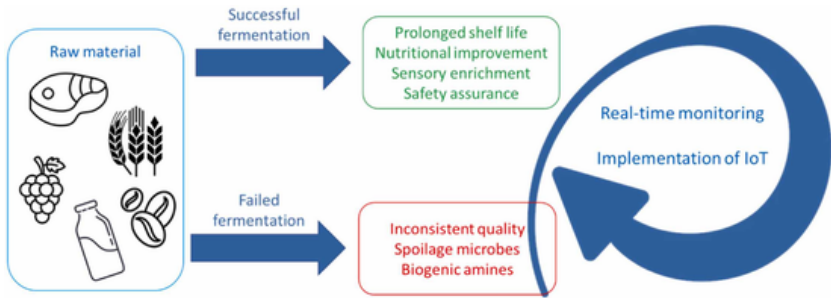


Fig. 1 Food fermentation: advantages and risks, highlighting the importance of real-time monitoring implemented in Internet of Things (IoT) solutions.

1). The selected starter cultures are critical in preserving the integrity, quality, and nutritional features of foods, especially in fresh products and fruits and vegetable beverages, which have a dynamic microbiome. These benefits are not only appreciated by traditional food cultures but are increasingly recognized and exploited by modern food science and technology (Anumudu et al., 2024; Dissanayake et al., 2025).

The improved safety and stability of perishable food products is due to the production of organic acids, such as lactic and acetic acid, which lower pH levels and create an inhospitable environment for many spoilage organisms and foodborne pathogens like *Listeria monocytogenes*, *Clostridium botulinum*, and *Salmonella*. LAB also produce bacteriocins, which are antimicrobial peptides that further enhance food safety (Aguirre-Garcia et al., 2024; Anumudu et al., 2024). In addition, carbon dioxide produced by fermenting yeasts can displace oxygen and reduce oxidation, thus delaying rancidity and spoilage. These microbial activities enable the natural preservation of foods without synthetic additives or refrigeration, making fermentation especially valuable in resource-limited and traditional settings (Ogwu & Ogunsola, 2024).

The nutritional value of fermented foods is enhanced through multiple pathways. Fermentation improves the bioavailability of micronutrients such as iron, zinc, and calcium by degrading anti-nutritional compounds like phytates and oxalates (Abbaspour, 2024). For example, sourdough fermentation of whole grains reduces phytic acid content, which otherwise chelates minerals and impairs their absorption (Lima, De Dea Lindner, & Martin, 2024). Fermentative microbes also synthesize beneficial compounds including B vitamins (such as folate, riboflavin, and vitamin B12), essential amino acids, and bioactive peptides

(Anumudu et al., 2024; Jang et al., 2024). The enzymatic breakdown of macronutrients, such as carbohydrates, proteins, and lipids, improves digestibility and allows for more efficient absorption of nutrients. In legumes and dairy products, fermentation reduces allergenic potential by hydrolyzing complex proteins into peptides and amino acids, rendering the food more tolerable for sensitive individuals (Jang et al., 2024).

Fermented foods serve as effective carriers of probiotic microorganisms, which include species from the genera *Lactobacillus*, *Bifidobacterium*, and *Saccharomyces* (Anumudu et al., 2024). These probiotics can colonize or transiently persist in the human gut, where they help modulate the intestinal microbiota, enhance gut barrier function, inhibit pathogens, and stimulate immune responses. Fermented foods like yogurt, kefir, kimchi, and kombucha often naturally contain or are supplemented with these beneficial microbes. Moreover, the fermented food matrix can help protect probiotics during passage through the acidic stomach environment (Aguirre-Garcia et al., 2024).

Fermentation is a major contributor to the sensory qualities of food. The microbial production of volatile compounds such as esters, aldehydes, ketones, and alcohols results in distinctive aromas and flavors associated with fermented products like cheese, wine, sauerkraut, and sourdough bread (Izah et al., 2024). These flavor compounds evolve throughout fermentation and are influenced by microbial strains, substrate composition, and fermentation conditions. Texture is also enhanced through microbial action. In yogurt and kefir, for instance, LAB produce exopolysaccharides that increase viscosity and creaminess. In fermented sausages, protein degradation by microbial enzymes leads to a tender, cohesive texture (Stegmayer et al., 2023). In sourdough bread, the interaction between LAB and wild yeasts results in a well-structured, airy crumb and a crisp crust (Lima et al., 2024).

Fermentation contributes significantly to the sustainability of food systems. By extending shelf life and reducing spoilage, fermentation helps mitigate food waste. It also provides energy-efficient alternatives to thermal processing (Sarma, Chatterjee, & Shrestha, 2024). In industrial contexts, fermentation is used to convert low-value raw materials and food processing by-products into high-value products such as biofuels, bioplastics, enzymes, organic acids, and flavor compounds. This valorization process supports circular economy principles and reduces environmental impact (Kumar et al., 2023; Salas-Millán & Aguayo, 2024). Furthermore, fermentation plays a critical role in the development

of plant-based and animal-free food innovations, offering alternatives to conventional animal products that are more resource-efficient and have a lower carbon footprint (Abbaspour, 2024).

2.2 Challenges and limitations of fermentation

Despite its protective nature, fermentation can fail if undesirable microbes gain dominance (Fig. 1). Improper hygiene, temperature control, or substrate preparation can lead to contamination by spoilage organisms or toxin producers such as *Clostridium* or *Bacillus* species. The production of biogenic amines, like histamine and tyramine, can also pose health risks in fermented meats, cheeses, and fish if not adequately monitored (Paramithiotis & Ray, 2024).

While fermentation reduces certain allergens and enhances digestibility, it can also lead to the accumulation of biogenic amines, particularly in aged cheeses, sausages, and wine. These compounds, including histamine and tyramine, may provoke migraines, rashes, or gastrointestinal symptoms in sensitive individuals. The risk is exacerbated in unregulated artisanal settings. Selecting non-decarboxylating strains and implementing proper ripening and storage protocols can reduce this risk (Abbaspour, 2024).

Traditional fermentations, especially those dependent on spontaneous microbial communities, can result in inconsistent product quality. Variables such as raw material composition, temperature, humidity, and indigenous microbial load influence the fermentation trajectory. This lack of reproducibility hinders scalability and regulatory approval for commercial applications. Employing standardized starter cultures and controlled fermentation systems mitigates this challenge, enabling greater predictability and batch-to-batch uniformity (Abbaspour, 2024; Gänzle et al., 2024). On the other hand, in continuous fermentation systems, industrial bacterial strains are prone to lose key production traits, compromising process stability and yield. Indeed, over time, certain microorganisms, especially those subjected to repeated subculturing, long-term storage, or stress conditions, can lose critical traits that are essential for their functional performance (Peng & Liang, 2020). In both cases, real-time monitoring through the implementation of IoT (Internet of Things) devices can enable precise control of the fermentation process, by tracking key parameters such as pH, redox potential, temperature, and nutrient concentration, thus providing early warnings of process deviations. The

use of these devices allows the enhancement of fermentation efficiency and consistency, ensuring that the production process remains within ideal conditions. Moreover, AI tools, like digital twins (i.e., virtual simulations of physical fermenters), allow for optimization of scale-up processes and adaptive control strategies, thereby minimizing waste and maximizing product yield (Abbaspour, 2024; Alasi et al., 2024).



3. Monitoring and control strategies

Despite the long-standing history of fermentation and its well-documented health benefits, actual scientific understanding of fermented foods remains incomplete and dispersed. Traditional fermentation practices, largely based on empirical knowledge, encounter limitations in achieving process consistency, industrial scalability, and comprehensive exploitation of microbial diversity (Zhang et al., 2025). Thus, the food industry encounters substantial challenges in ensuring safety and quality throughout the fermentation process. Conventional monitoring and control methods are often limited by their lack of real-time responsiveness, resulting in suboptimal process efficiency, delayed intervention in the event of microbial or physicochemical deviations, and elevated risks of contamination. Moreover, manual monitoring procedures are susceptible to human error, further compromising process reliability. These limitations underscore the need for advanced, real-time analytical technologies capable of enhancing control precision and ensuring consistent fermentation outcomes in compliance with food safety standards (Abbas et al., 2024). Innovations in sensor systems, AI, machine learning (ML), and digital twin frameworks are enabling unprecedented precision, efficiency, and product quality in fermentation-based food production (Abbaspour, 2024; Alasi et al., 2024).

3.1 Traditional monitoring techniques

Traditionally, fermentation monitoring mainly relies on simple measurements of pH, optical density, temperature, and redox potential. These variables provide indirect insight into microbial activity and metabolic progression. However, while pH serves as a rapid and well-understood indicator of process deviations, it does not elucidate the underlying causes of such deviations, which is crucial for evaluating both biological and engineering performance in bioprocess monitoring. Similarly, optical

density provides a rough estimation of broth turbidity, often interpreted as an index for biomass concentration; however, it does not accurately reflect the physiological state of the bacterial culture. Furthermore, optical density measurements are typically performed off-line, introducing a time lag between sampling and data acquisition, which usually takes place in a laboratory setting (Narayana, Christensen, Skov, & van den Berg, 2019).

Traditional analytical techniques used in biotechnological industries for product quantification and quality control (e.g., plate counting, high-performance liquid chromatography - HPLC, and DNA-based assays) are generally performed post-process. These methods are labor-intensive, time-consuming, and subject to high variability. Moreover, their throughput is often insufficient to accommodate the increasing demand for monitoring multiple parallel production lines (Narayana et al., 2019).

Manual sampling for microbial plate counts, sugar content, and product yield remains widespread in small-scale operations. In the fermentation of kombucha, for instance, manual sugar testing using HPLC, enzyme methods, and anthrone-sulfuric acid method remain off-line standard procedures for determining residual sugar concentration and fermentation completeness (Zhao et al., 2023).

In yogurt production, periodic sampling and off-line acid-base titrations or pH measurements are used to monitor LAB metabolic activity and product acidification. Lactic acid, carbohydrates (i.e., lactose and galactose), and bacterial concentrations can be also evaluated as key indicators of fermentation progress, but they are not routinely measured, being expensive and time-consuming (Grassi et al., 2013).

In cocoa bean fermentation, frequent manual turning of fermentation boxes and temperature logging are practiced to ensure oxygenation and control of microbial succession. These are critical to flavor development and are guided by sensory inspection, manual pH readings, and temperature measurements taken at various depths. The sucrose concentration reduction is usually measured in total soluble solids (°Brix) and it is an index of microbial activity (Pinto et al., 2024).

In beer brewing and wine fermentation, traditional monitoring involves daily gravity measurements with hydrometers or refractometers, visual observation of foaming and bubbling activity (indicative of CO₂ release), and taste evaluations to assess fermentation progress and potential contamination. These artisanal methods are still commonly practiced

in craft operations and hobbyist setups (Gallego-Martínez et al., 2024; Harris et al., 2024).

While accessible and low-cost, these traditional approaches are labor-intensive, time-delayed, and prone to contamination. For instance, off-line sugar measurements using chemical reagents require repeated handling, raising contamination risks and introducing variability between operators, as specifically reported for kombucha fermentation (Zhao et al., 2023).

The lack of real-time feedback limits responsiveness and hampers consistent product quality, especially under variable environmental conditions. Furthermore, traditional methods provide single-point data, making it difficult to capture the dynamic microbial and biochemical changes that occur continuously during fermentation. The absence of data integration across physical and biochemical variables also makes it challenging to implement predictive or closed-loop control strategies in traditional systems (Zhang et al., 2025).

3.2 Advanced monitoring techniques

In recent years, significant improvements in-line, real-time monitoring systems allowed precise control of fermentation parameters, overcoming the issues associated with traditional monitoring methods. These systems include (Khan et al., 2024; Lin & Sun, 2020; Narayana et al., 2019; Niyigaba, Küçükgoz, Kołozyn-Krajewska, Królikowski, & Trzaskowska, 2025):

- Miniaturized and integrated bio- and chemo-sensors for continuous measurement of temperature, pH, biomass, and gases (e.g., CO₂, NH₃, O₂), eliminating the need for manual sampling and reducing contamination risks. These sensors provide high sensitivity and specificity for detecting fermentation endpoints, spoilage events, or contamination;
- NIR and visible-NIR (vis-NIR) spectroscopy for non-invasive and high-speed tracking of fermentation kinetics, such as sugar consumption, production of compounds from biochemical conversions, and bacterial concentration;
- Mid-infrared (MIR) and Raman spectroscopy for tracking specific metabolite transformations, such as lactic acid and volatile compound production.

- Electronic-noses (e-noses) and electronic-tongues (e-tongues) mimic human sensory systems using sensor arrays that capture volatile organic compounds and taste-relevant molecules to assess aroma profiles and fermentation maturity in products like wine, cheese, and kombucha;
- Omics technologies, such as metagenomics, transcriptomics, proteomics, and metabolomics, to reveal microbial community dynamics and metabolic pathways. These tools inform microbial selection, strain engineering, and process optimization.

AI, including ML and deep learning (DL) models, is increasingly integrated into fermentation systems to interpret large volumes of process data and inform decision-making (Niyigaba et al., 2025). These tools reduce the time and resources required for traditional trial-and-error optimization and open the door to fully automatic fermentation systems. ML and DL algorithms enhance pattern recognition, error detection, and adaptive control. Popular techniques include:

- Principal component analysis (PCA): It is widely used as a pattern recognition step and to reduce the dimensionality of spectral datasets, thus facilitating better training of ML models (Zhao et al., 2023); furthermore it could be applied to construct multivariate statistical process control (MSPC) charts, based on Hotelling's T^2 and Q residuals statistics, which are powerful tools for monitoring and controlling complex processes involving multiple correlated variables (Ferrer, 2007);
- Partial least square regression (PLSR): Commonly used for linear modeling; it offers fast computation but may underperform in nonlinear systems (Lin & Sun, 2020);
- Artificial neural networks (ANNs) and convoluted neural networks (CNNs): Nonlinear models that handle high-dimensional and non-linearly correlated data more effectively (Zhao et al., 2023);
- Support vector machines (SVMs): Although less common than PLSR and ANN in fermentation, SVMs have demonstrated strong generalization capabilities in classifying fermentation stages, particularly when using NIR-derived feature sets in systems like beer brewing and fermented beverages (Harris et al., 2024);
- Multivariate curve resolution-alternating least squares (MCR-ALS): Employed in conjunction with NIR spectroscopy to resolve overlapping spectral signals. This chemometric tool allows for deconvolution

of spectra into pure component profiles, aiding the interpretation of fermentation phenomena (Jaumot, De Juan, & Tauler, 2015);

- Hybrid (or gray-box) modeling approaches: Hybrid models combine mechanistic knowledge of fermentation kinetics with data-driven techniques, thus integrating the strengths of both approaches to enhance the monitoring and control of food fermentation processes. These models utilize fundamental biochemical and microbial kinetic equations to describe system behavior, while employing ML or statistical methods to capture complex, non-linear patterns and compensate for unmodeled dynamics or measurement noise. This synergy improves prediction accuracy, robustness, and adaptability under variable processing conditions (Albino et al., 2024; Herrera-Ruiz, Fontalvo, & Prado-Rubio, 2024).
- Explainable artificial intelligence (XAI): Tools focused on making AI systems, especially complex models like DL, more transparent, interpretable, and trustworthy to human users. The goal is to provide understandable insights into how and why AI models make decisions, particularly in high-stakes fields like healthcare, finance, autonomous vehicles, and food process control, where black-box decisions are unacceptable without justification. Common XAI tools include feature importance metrics (e.g., Shapley additive explanations – SHAP; local interpretable model-agnostic explanations – LIME), visualization techniques (e.g., saliency maps in image classification, partial dependence plots – PDPs, t-distributed stochastic neighbor embedding/uniform manifold approximation and projection - t-SNE/UMAP for visualizing internal embeddings), rule-based explanations (e.g., decision tree surrogates for neural networks; rule extraction algorithms; counterfactual explanations), and model-specific tools, like attention maps in transformer models, and gradient-weighted class activation mapping (Grad-CAM) for CNNs (Gunning & Aha, 2019).

Big data-driven process operations can drive digitalization in food industries. In process industries, digitalization initiatives primarily aim to enhance production throughput, efficiency, and product quality without necessitating additional physical infrastructure. Among these initiatives, digital twins have emerged as a pivotal concept. Digital twin technology refers to the creation of a digital replica of a physical system, such as a product, process, or entire plant. This digital construct enables real-time data exchange, simulation, and decision-making. There are three main forms of digital constructs (Udugama, Kelton, & Bayer, 2023):

- Digital model: It uses off-line data without real-time connectivity;
- Digital shadow: It receives real-time data from the physical process but cannot influence it;
- Digital twin: It features bi-directional data exchange, allowing the digital model to influence real-time operations through feedback loops.

Digital twins help optimize decisions throughout the lifecycle of food products, from formulation to large-scale production. They enable simultaneous consideration of sensory qualities, nutritional value, safety, circular production, and market dynamics. Multi-scale models integrate data across layers, from consumer behavior to plant operations, enabling dynamic adjustments in response to changes in demand, raw material variability, or quality parameters. Moreover, predictive models allow for early-stage optimization of new food products and help reduce costs related to scale-up and design validation. Digital twins help also monitor and minimize energy usage, material waste, and environmental impact through precise control of operations. Despite these promising advances, several challenges remain (Udugama et al., 2023; Zhang et al., 2025):

- High initial investment in digital twin and AI infrastructure may limit adoption by small- and medium-sized enterprises;
- The complexity of microbial ecosystems demands robust, adaptive modeling that integrates multi-omics data, which is still in early-stage deployment across the food industry;
- Greater efforts are required in data integration, interoperability, and cybersecurity for real-time systems operating across multiple scales and locations.

Ongoing advances in sensors, AI, and process modeling are key enablers for shifting from conventional to modern monitoring systems (Udugama et al., 2023), which are of paramount importance also in boosting the application of PAT in the food industry. PAT was initially developed by the Food and Drug Administration (FDA) for the pharmaceutical sector; then, it has gained increasing relevance in the food industry as a transformative approach to quality control. PAT emphasizes real-time measurement and control of critical quality and performance attributes during production, shifting quality assurance from traditional feedback mechanisms to predictive, model-based strategies. This real-time, data-driven control fosters enhanced process understanding, robustness, and consistency, facilitating innovation through the Quality by Design (QbD) approach. QbD builds upon PAT by promoting a systematic de-

sign of food products based on the prior identification and control of critical quality attributes, supported by thorough process understanding. Together, PAT and QbD offer significant benefits for the food industry, including improved product quality, safety, authenticity, and regulatory compliance, while simultaneously reducing production costs and enhancing resource efficiency. Nevertheless, the inherent complexity of food matrices, due to the variability of raw materials, intricate processing dynamics, and perishability, poses unique implementation challenges that must be addressed through advanced modeling and control strategies (Grassi & Alamprese, 2018).

The development of innovative and advanced solutions has been markedly accelerated by the advent of Fourth Industrial Revolution (Industry 4.0) technologies, which encompass AI, cyber security, augmented reality, big data analytics, cloud computing, robotics, the IoT, additive manufacturing (3D printing), and biotechnology. While the implementation of such technologies is well-established across several industrial sectors, the integration of Industry 4.0 in agriculture and the food industry remains in a developmental phase, with ongoing efforts aimed at exploration and optimization (Adeleke, Nwulu, & Adebo, 2023; Hassoun, Dankar, Bhat, & Bouzembrak, 2024).

The modern food supply chain faces critical challenges requiring technological innovation to ensure sustainability, efficiency, and security. The IoT emerges as a transformative solution, particularly within the agricultural sector, where dynamic and complex workflows demand real-time, responsive management. IoT refers to a network of compact, low-power electronic devices, each functioning as a "smart node", that wirelessly collect, process, and transmit data via cloud infrastructure. In agriculture, core functions of IoT include observation, control, and actuation, which facilitate continuous monitoring of the supply network and enhance real-time data exchange. This capability significantly reduces losses, supports food safety, and improves overall traceability and visibility across the food chain. When integrated with complementary technologies such as big data analytics, blockchain, and ML, IoT enables the advancement of smart agriculture, achieving key objectives like increased productivity, water conservation, and reduced pesticide usage. Despite its potential, current IoT implementations in the food sector remain nascent and fragmented, necessitating comprehensive integration to realize full-scale benefits across food safety, storage, distribution, and processing. This highlights the pressing need for coordinated efforts to modernize the

agri-food ecosystem through IoT-enabled innovation (Adeleke et al., 2023).

As for food fermentation, Schorn-García et al. (2024) emphasized how PAT can enable in-line, non-invasive, and continuous monitoring of key physicochemical parameters. Their work reviewed a spectrum of PAT-compatible sensors, including Raman, NIR, and mass spectrometry systems, and highlighted case studies where PAT was used to enhance the reproducibility and control of microbial fermentation. Particularly, the integration of PAT into bioreactor systems for microbial biomass and metabolite tracking demonstrated strong potential for closed-loop control. Bockisch, Kielhorn, Neubauer, and Junne (2019) provided an early but comprehensive perspective on PAT deployment in industrial fermentation. The review emphasized the transition from empirical control strategies toward model-based control, supported by real-time data analytics. The study illustrates how sensors embedded in bioprocesses reduce process variability while improving QbD compliance. Together, these studies highlight the shift from static, end-point assays toward dynamic, AI-augmented monitoring frameworks capable of capturing real-time biochemical and microbial changes. They demonstrate how modern tools bridge the gap between empirical practices and precision fermentation, ultimately enabling higher consistency, traceability, and adaptability across diverse fermented food systems.



4. NIR spectroscopy as a tool for PAT in food fermentations

Vibrational spectroscopic methods, such as NIR, MIR, Raman and terahertz spectroscopies, and hyperspectral imaging are gaining popularity in bioprocess monitoring following the PAT approach, since they enable rapid, non-invasive, and multi-component analysis of fermentation processes (Narayana et al., 2019). Vibrational spectroscopy provides a molecular fingerprint of a sample and holds significant potential for its quantification, qualification, characterization, and structural elucidation. Due to its minimal sample preparation requirements, simplicity, non-destructive nature, and rapid analysis capabilities, vibrational spectroscopy has been widely employed for both qualitative and quantitative assessment of diverse agricultural and food matrices (Lin & Sun, 2020).

In particular, NIR spectroscopy has emerged as one of the most powerful analytical tools in the non-destructive, real-time monitoring of food fermentation. Its advantages over conventional wet chemistry (i.e., rapid acquisition, minimal sample preparation, multi-component detection, potential for automation) make it particularly suitable for dynamic bioprocesses where chemical and physical transformations evolve continuously. NIR spectroscopy operates in the 780–2500 nm wavelength ($4000\text{--}12,800\text{ cm}^{-1}$) range and relies on molecular overtone and combination vibrations, particularly those of C-H, O-H, and N-H bonds. In food fermentation, this enables the quantification of carbohydrates, organic acids, alcohols, and water content, all critical indicators of microbial activity (Zhao et al., 2023).

To predict key fermentation parameters based on spectroscopic data, data-driven models are employed (Fig. 2). NIR spectra are indeed typically complex, with overlapping signals and collinearity. The use of AI models is therefore necessary to extract the information of interest.

To improve the spectra quality, different preprocessing methods can be used, such as standard normal variate (SNV), scaling, multivariate scatter correction (MSC), smoothing (Savitzky–Golay – SG, moving average, and median filter), detrending, first and second derivatives. Feature wavelength selection can also be useful to decrease the computation load and increase predicting accuracy by removing low informative bands and extracting the most meaningful wavelengths. To the aim, PLSR, PCA, stepwise regression (SR), successive projection algorithm

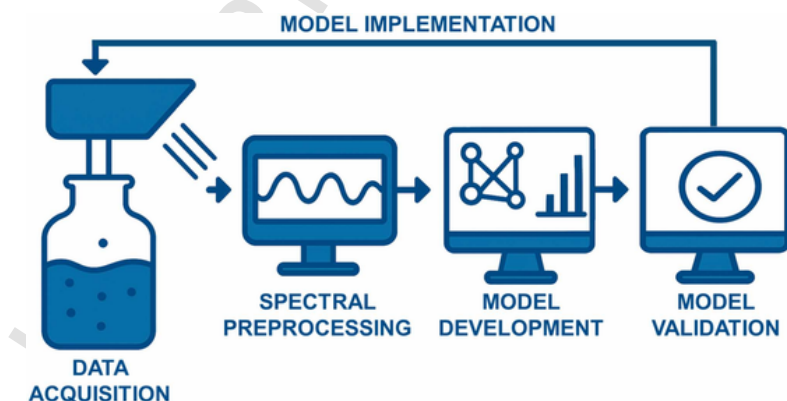


Fig. 2 Workflow of the use of NIR spectroscopy in food fermentation monitoring.

(SPA), uninformative variable elimination (UVE), and genetic algorithm (GA) can be used (Lin & Sun, 2020).

Supervised calibration models are generally categorized into two main types: classification and regression models. The goal of classification is to assign samples to discrete categories or classes, whereas regression approaches aim to predict continuous numerical values. Supervised classification methods include linear discriminant analysis (LDA), partial least squares discriminant analysis (PLS-DA), SVMs, K-nearest neighbors (KNN), soft independent modeling of class analogy (SIMCA), and random forest algorithms. Regression models encompass both linear and non-linear techniques. Linear regression methods include multiple linear regression (MLR), principal component regression (PCR), and PLSR. In contrast, nonlinear regression approaches involve ANNs, support vector regression (SVR), and least squares support vector machines (LS-SVM) (Lin & Sun, 2020).

Stability and performance optimization of the model are typically assessed using cross-validation, an iterative validation procedure. Afterwards, prediction performance and robustness are determined by external validation procedures (Westad & Marini, 2015). Performance of classification models is assessed by verifying if samples belonging to the class of interest are correctly assigned or mislabeled. Thus, the common diagnostic metrics include sensitivity, specificity, and accuracy (Oliveri, 2017), which should be evaluated at each step of model development. Common evaluation metrics for regression models include the root mean square error of calibration (RMSEC), cross-validation (RMSECV), and prediction (RMSEP), along with the corresponding coefficients of determination for calibration (R^2_c), cross-validation (R^2_{cv}), and prediction (R^2_p). The optimal model is usually identified based on achieving the highest R^2 values and the lowest RMSE values (Lin & Sun, 2020).

4.1 Examples of NIR spectroscopy applications in food fermentation

Table 1 summarizes some recent applications of NIR spectroscopy in food fermentation monitoring and control. Although mainly developed at a lab-scale, these applications show the potential of NIR spectroscopy for the development of on-line monitoring methods in line with the PAT approach. To make the text easier to navigate, the applications are presented in alphabetical order both in the table and in the following text.

Table 1 NIR spectroscopy applications in food fermentation.

Food product	NIR application	References
Alcoholic beverages	Monitoring the entire craft beer production process by means of multivariate control chart.	França et al. (2021)
	Investigation of temporal trends and relationships with brewing parameters in homemade production.	Cavallini et al. (2025)
	Quantification of key brewing components during the mashing and boiling stages of wort.	Zhou et al. (2024)
	Beer fermentation endpoint prediction.	Harris et al. (2024)
	Monitoring sugar-alcohol transformations and phenolic changes in winemaking.	Alfieri et al. (2025), Gallego-Martínez et al. (2024), Littarru et al. (2023)
	Real-time alcohol monitoring during sake production.	Naito et al. (2024)
	Prediction of key parameters during fermentation of pineapple wine.	Kasemsumran et al. (2022)
	Dough fermentation state assessment.	Castro-Reigía et al. (2024), Chang et al. (2021), Jiang et al. (2025)
Dairy fermented products	Dynamic modeling of kefir fermentation.	Gorla et al. (2023), Grassi et al. (2013), Grassi et al. (2014), Muncan et al. (2021)
	Monitoring and quality control of yogurt fermentation dynamics.	
Dry fermented sausages	Process stage prediction.	González-Mohino et al. (2020)

Food product	NIR application	References
Fermented plant materials	Monitoring bacterial population shifts and antioxidant profile during cocoa bean fermentation. Tracking microbial succession and volatile compounds during coffee fermentation. Catechins and theanine content prediction in differently fermented teas. Monitoring key chemical components across black tea processing stages.	Pinto et al. (2024), Tirado-Kulieva et al. (2024), Chen et al. (2021), Wang et al. (2021)
Kombucha	Sugar content prediction using hybrid models. Real-time prediction of sugar and bacterial biomass.	Zhao et al. (2023), Zhao et al. (2025)
Vinegar	Prediction of ethanol content and total acidity throughout the entire fermentation cycle.	Menozzi et al. (2024)

Fermentation is a cornerstone process in the production of **alcoholic beverages**, such as beer, wine and sake. The precise control of fermentation parameters, especially sugar conversion to ethanol and the formation of flavor-active compounds, is essential for ensuring consistent quality. Traditionally, these processes have been monitored using classical laboratory techniques like gas chromatography–mass spectrometry (GC-MS), HPLC, sensory evaluations, and various wet chemistry techniques to measure key parameters like alcohol content, pH, acidity, and density. While accurate, these methods are unsuitable for on-line monitoring. The use of NIR spectroscopy, especially in the winemaking field, is consolidated (Cozzolino, Damberg, Janik, Cynkar, & Gishen, 2006), and recent advances have also demonstrated that it can be a valid alternative for non-destructive, rapid, and cost-effective monitoring in real time. The development of portable NIR devices has also democratized the technology, making it accessible to homemade processes and small-scale producers. These handheld instruments can be operated via smartphone applications and are capable of generating immediate, meaningful insights

into the brewing process with minimal training (Cavallini, Cavallini, & Savorani, 2025).

França, Grassi, Pimentel, and Amigo (2021) developed a comprehensive approach for monitoring the entire craft beer production process, including mashing, circulation, boiling, fermentation, and carbonation, by a benchtop NIR device. Based on spectral data, a multivariate control chart was constructed to track beer development batch by batch. Four batches under normal operating conditions were used to build the model, and three external batches were used for validation (i.e., two with intentional disturbances and one under standard conditions). NIR spectra were also used to predict soluble solid content by PLSR. The findings highlight the method robustness, simplicity, and effectiveness for holistic monitoring and control of the brewing process. Even though the sampling was at-line performed, the system could be easily transformed into an in-line one.

Cavallini et al. (2025) examined the use of the handheld SCiO NIR sensor to monitor fermentation in homebrewed beers. Using PCA, they showed how even simple analytical tools could reveal temporal trends corresponding to different fermentation stages. The effect of temperature changes during fermentation was also revealed. Scattering information contained in the spectra was related to bubble formation and size. However, the Authors noted that variations in raw materials, such as the use of distinct malt extracts from different manufacturers or tailored for specific beer styles, as well as environmental conditions, including seasonal brewing periods and differences in storage temperature and light exposure, may lead to markedly divergent fermentation outcomes. From a computational standpoint, a dedicated application capable of performing PCA or other process monitoring analyses on collected data is essential for end-users. The development of a smartphone-based application facilitating automated data acquisition and interpretation represents a highly promising direction. Although the SCiO “Applets” integrated within the “SCiO Pocket Molecular Sensor” application offer some functionality in this regard, current customizable applets do not support real-time process control capabilities. The on-line or in-line sampling was not feasible due to both the NIR instrument used and the homebrewed process.

Zhou et al. (2024) applied NIR and other spectroscopic methods (Raman and UV–Vis) for monitoring Qingke (i.e., cultivar of hulless barley that grows at high altitudes) beer fermentation. Their work focused on quantifying key brewing components (i.e., reducing sugar, free amino

nitrogen, and total phenolic) during the mashing and boiling stages of wort, through ANN, PLSR, and LS-SVM models. Actually, contents of these components change rapidly, and conventional testing methods can't be used for real-time monitoring of the process. The ANN model demonstrated the highest performance in quantitative prediction, outperforming the PLSR model, while the least stable results were obtained with LS-SVM. This can be attributed to the complex chemical transformations occurring in the wort during the mashing and boiling stages, where the concentrations of critical compounds do not follow a linear progression. Although these nonlinear variations are captured within the spectral data, the ANN model, being inherently nonlinear due to its activation functions, exhibits a superior ability to model the complex relationships between input features and target variables. The results then proved the reliability of spectroscopy and chemometrics for monitoring and quality control of beer brewing, thus ensuring high quality and stable production. Furthermore, the use of the liquid probe working in diffuse reflection connected to a benchtop instrument could be envisioned for on-line applications.

Harris et al. (2024) developed a method using handheld NIR spectroscopy and ML models to analyze beers without opening bottles, preventing quality assurance issues, fraud, and origin concerns. Type of fermentation, intensity of 16 sensory descriptors, and volatile aromatic compounds measured by GC-MS were all predicted with high accuracy (up to 99% of correct classification for fermentation type, and correlation coefficients between 0.92 and 0.94 for the other responses) by applying ANN models. However, a limited number of samples were used (i.e., 25 beers), thus additional data are needed to better represent real-world variability.

Littarru et al. (2023) investigated the application of NIR spectroscopy for real-time, on-line monitoring of fermentation in **winemaking**. NIR spectroscopy was used to calculate PCR models for the prediction of the concentration of key fermentation metabolites including glucose, fructose, anthocyanins, and polyphenols. Despite the limited number of samples, the developed models demonstrated quite good prediction capability ($R^2_p > 0.74$), highlighting the potentiality of this technology, which must be tested with a larger dataset to capture a wider range of chemical scenarios and enhance the model robustness. Alfieri et al. (2025) compared a low-cost NIR prototype with a commercial FT-NIR spectrometer. While the prototype showed slightly reduced performance,

it still achieved strong predictions for anthocyanins (ratio of performance to deviation $RPD = 5.49$) and polymeric pigments ($R^2_p = 0.87$, $RMSEP = 0.15$), confirming its potential for real-time process control. The usefulness of NIR spectroscopy to monitor chemical changes occurring during oenological processes was recently reviewed by Gallego-Martínez et al. (2024), who highlighted its application in tracking malolactic fermentation, sugar-alcohol transformations, and phenolic maturation stages. The ability to continuously monitor volatile and non-volatile profiles can enable winemakers to make timely interventions, optimizing aroma and mouthfeel in the final product.

Naito et al. (2024) introduced a novel NIR method for directly measuring **sake** mash during brewing using two optical measurement systems: a diffuse reflection and a transreflectance method. To mitigate the effects of water absorption and multiple scattering due to physical properties of sake mash, the difference spectra of the diffuse reflection and transreflectance spectra were calculated. A PLSR model achieved a $RMSEP$ value of 0.76% v/v for alcohol prediction, with a significant improvement compared to diffuse reflectance alone ($RMSEP = 1.99\%$ v/v). This method allowed real-time alcohol monitoring in unfiltered, turbid mash samples, overcoming one of the key limitations of traditional NIR applications in sake production.

Kasemsumran et al. (2022) used FT-NIR spectroscopy with a transreflectance probe to simultaneously predict four key parameters during fermentation of **pineapple wine**: ethanol, total soluble solids, total acidity, and total volatile acids. The optimized PLSR models yielded $R^2_p > 0.97$ for ethanol, $RPD > 4$ for all parameters, $RMSEP$ as low as 0.087% for ethanol, enabling accurate online monitoring without sample preparation.

Overall, NIR spectroscopy offers a fast, efficient, and cost-effective solution for monitoring the production process of alcoholic beverages. Its adaptability to both industrial and artisanal or homemade applications, coupled with its ability to integrate with digital tools and AI, makes it an indispensable component of modern analytics in this field.

NIR spectroscopy has emerged as a promising tool for non-invasive and rapid assessment of **bread dough** fermentation, providing a scientific basis for quality control and process optimization in both traditional and modern baking systems. Conventional methods for monitoring the leavening step rely heavily on manual procedures, making them labor-intensive and inefficient. Often, a bakery expert judges the quality of doughs before baking, making subjective the assessment. Rheo-fermen-

tation analysis presents a valuable alternative by delivering precise parameters that reflect the quality attributes of baked goods (Jiang et al., 2025). Nevertheless, this technique is limited by its time-consuming nature and the need for extensive sample sets. In contrast, recent studies by Castro-Reigía et al. (2024), Chang et al. (2021), and Jiang et al. (2025) demonstrate how NIR spectroscopy, integrated with multivariate analysis and ML, can effectively monitor dough leavening stages and predict rheological properties critical to product quality in a rapid, non-invasive, and cost-effective way.

In the study by Chang et al. (2021), NIR spectroscopy combined with supervised learning algorithms (i.e., SVM and KNN) was applied to monitor the fermentation of Chinese steamed bread. Through different preprocessing techniques and variable selection methods, the Authors confirmed that reasonable monitoring model of dough fermentation could be established. SG-smoothing was found as the best pretreatment method to eliminate the physical interference and noise of NIR spectra. Thirteen characteristic features were finally selected from the spectra, thus reducing the computational load of the model and improving their performance. The SVM model to distinguish among under-, optimal-, and over-fermentation stages achieved 94% accuracy in the training set and 92% in the prediction set, outperforming the KNN model. Thus, the integration of NIR spectroscopy with supervised learning algorithms provides an objective alternative to manual assessment for determining the fermentation state of dough, minimizing the variability associated with human judgment. Moreover, this approach enables rapid, real-time monitoring of the fermentation process, thereby supporting increased automation and consistency in Chinese steamed bread production.

The fermentation stage of dough was the focus also of the work by Castro-Regía et al. (2024), but in industrial bread production. The Authors implemented a PLS-DA classification model based on NIR spectra collected at-line in a bakery setting using a commercial NIR system. In the optimal case, sensitivity and specificity exceeded 86% for all classes in the prediction set. This study was conducted as a proof of concept for the near-future integration of a NIR spectrometer within the fermentation chamber of an industrial bakery production line. The proposed approach involves acquiring a single spectral measurement from each dough sample to estimate its fermentation status. This strategy enables the real-time identification of underperforming doughs prior to baking, allowing for timely adjustments to fermentation conditions (e.g., temperature and hu-

midity) to optimize product quality and to reduce energy consumption and product waste.

Jiang et al. (2025) explored the use of NIR spectroscopy in monitoring dough fermentation in 3D-printed bakery products. SVM and PLSR models were trained on NIR data differently preprocessed to predict key rheological parameters: storage modulus (G'), loss modulus (G''), complex viscosity (η^*), and loss factor ($\tan \delta$). The SVM model outperformed the PLSR one, achieving R^2_p values higher than 0.93 for all the rheological parameters except $\tan \delta$ ($R^2_p = 0.67$), by using 27–39 selected variables depending on the considered response.

To sum up, NIR spectroscopy offers several notable advantages when applied to dough fermentation monitoring. As a non-destructive and rapid technique, it allows measurements to be taken without altering the dough structure, preserving sample integrity throughout the process. Its capacity for real-time analysis enables continuous observation of fermentation dynamics, which is particularly beneficial for industrial applications. Furthermore, the method requires minimal sample preparation, thereby streamlining workflows and enhancing operational efficiency on the production line. Another key strength lies in its compatibility with multivariate analytical tools and ML techniques, which enable the effective modeling of complex, nonlinear relationships between spectral data and dough properties. This analytical power supports process automation, making it suitable for integration with smart sensors in-line quality control systems.

Dairy fermented products such as yogurt and kefir rely on complex biochemical transformations primarily driven by LAB. Accurate monitoring of these fermentations is critical for product quality, safety, and consistency. Traditionally, fermentation control has relied on pH measurements, titratable acidity, microbial counts, and rheological analysis. While effective, these methods are time-consuming, labor-intensive, and not suitable for real-time, in-line monitoring. The advent of NIR spectroscopy, combined with chemometrics, has introduced a non-invasive, rapid alternative for process control.

The use of handheld NIR spectrometers as PAT tools in **kefir** fermentation was evaluated by Gorla, Ferrer, and Giussani (2023), providing guidance on best practices and key steps for enabling process monitoring. Key aspects relevant to batch processes, such as specific growth rate, substrate consumption, and oxygen transfer, were systematically investigated and discussed, with a dual focus on enhancing process understand-

ing and exploring opportunities for real-time monitoring and endpoint determination. By integrating various statistical tools, the meaningful information was extracted from the spectral data, facilitating the identification of correlations with the chemical and physical transformations occurring during the process. Additionally, specific spectral features associated with kefir fermentation within the examined wavelength range were characterized and interpreted. Ultimately, miniaturized NIR spectroscopy was shown to effectively capture relevant information pertaining to kefir fermentation, enabling the detection of variations in process conditions.

The review by Mehra et al. (2022) highlights the importance of advanced analytical tools, including Fourier transform (FT)-NIR spectroscopy, for the real-time, non-destructive monitoring of fermentation dynamics and quality control in **yogurt** production. In particular, the works by Grassi et al. (2013) and Grassi, Alamprese, Bono, Casiraghi, and Amigo (2014) demonstrated that it is possible to monitor lactic acid fermentation by FT-NIR spectroscopy coupled with kinetic models based on principal components or MCR-ALS, enabling the identification of deviations in key quality parameters. Similarly, Muncan, Tei, and Tsenkova (2021) demonstrated the effectiveness of aquaphotomics based on FT-NIR spectroscopy as a real-time, non-invasive tool for monitoring the yogurt fermentation process. Moving window PCA (MWPCA) was employed to track temporal spectral changes, enabling detection of three distinct fermentation stages aligned with bacterial growth dynamics and acidification. Spectral variations were largely attributed to water structural changes and light scattering from evolving casein micelles, thus reflecting key physicochemical events in yogurt production. The dissimilarity index derived from MWPCA loadings revealed rapid spectral transitions during the logarithmic phase of microbial growth, corresponding to significant acidification and structural transformations. These findings highlight the potential of NIR spectroscopy, combined with aquaphotomics, for robust and automated quality control in yogurt production.

Summarizing, NIR spectroscopy offers several important advantages for monitoring dairy fermentation processes. Its non-destructive nature enables real-time, in-line assessments without disrupting the sample, allowing for continuous tracking of fermentation progress. This technique is capable of simultaneously monitoring multiple constituents, including sugars, organic acids, and protein-related changes, making it a powerful multiparametric tool. Once the system is established, spectral acquisition

is rapid and cost-effective, offering high throughput with minimal per-sample expense. Furthermore, parameters derived from NIR data have been shown to strongly correlate with conventional measurements such as pH, titratable acidity, lactic acid concentration, and rheological properties, confirming its reliability as an alternative to traditional methods.

In the production of **dry-fermented sausages**, fermentation and drying phases are important to define the sensory properties of the final products. Most of these sausages are produced using traditional methods, typically with limited mechanization and minimal control over the final product, which could lead to high variability in final product quality. Accurate data on the quality of these products can derive from several analytical methods, such as physicochemical, chromatography, mass spectrometry, or sensory ones, but they are destructive, expensive, tedious, time- and solvent-consuming. Thus, González-Mohino et al. (2020) proposed a NIR-based approach for monitoring the production of traditional dry-fermented sausages and classifying samples by processing stage. The use of a handheld NIR spectroscopy device, combined with PLS-DA, allowed for a correct classification of the stage of the process with 100% sensitivity and specificity in prediction. The proposed approach may be useful to determine when to move from one stage to the next one, but further studies are needed before upscaling to an industrial setup.

Several **plant materials** need fermentation to develop peculiar sensory properties. For instance, the quality of **cocoa beans** is influenced by both genetic factors and post-harvest processing, particularly fermentation and drying. Genetic variation affects the biochemical composition of the beans (e.g. content of proteins, lipids, carbohydrates, and phenolic compounds), which in turn influences microbial activity and biochemical transformations during fermentation, essential for flavor and color development. However, practices such as mixing fermented with unfermented beans and co-planting different genotypes hinder the identification of high-value varieties and complicate quality control (Pinto et al., 2024). To address these issues, NIR spectroscopy has emerged as a rapid and effective tool for predicting biochemical quality traits and supporting the characterization, classification, and authentication of cocoa and chocolate products. The study by Pinto et al. (2024) explores the application of vis-NIR spectroscopy for discriminating between fermented and unfermented cocoa beans and for classifying genetic profiles of cocoa genotypes from the Brazilian Amazon. Spectral data were collected on

whole beans, and chemometric techniques including PLS-DA, LDA, and PCA were used for classification and data interpretation. Vis-NIR spectroscopy successfully distinguished fermented from unfermented beans with high sensitivity and specificity across multiple spectral windows (99.2–100% accuracy). Notably, LDA using only two wavelengths from either visible or NIR ranges (e.g., 472 and 636 nm or 2096 and 2278 nm) achieved comparable performance (100% correct classification), enabling potential development of low-cost spectral sensors. This non-destructive technique supports the industry increasing emphasis on sustainable practices, operational efficiency, and the implementation of environmentally conscious technologies, paving the way for an on-line adoption to continuously monitor the cocoa bean fermentation.

Similarly, **coffee bean** fermentation is critical to final cup quality, but it is often managed visually, leading to inconsistent outcomes. The study by Tirado-Kulieva, Quijano-Jara, Avila-George, and Castro (2024) aimed to improve fermentation monitoring using NIR spectroscopy combined with chemometric models to predict key fermentation parameters (i.e., pH and total soluble solids) in three *Coffea arabica* varieties (Typica, Caturra, Catimor). NIR spectroscopy was employed to monitor fermentation over 24 h. PLSR was used to predict pH and total soluble solids from full and reduced spectra. To improve model performance and reduce computational complexity, three variable selection techniques were tested. A novel method introduced in this study (i.e., Covering Array Feature Selection, CAFS) was particularly effective due to its ability to select a minimal highly informative set of wavelengths distributed across the spectrum (22–47 variables), allowing for robust model construction with high prediction accuracy (RMSEP ranges from 0.096 to 0.158 and from 0.688 to 1.059 for pH and soluble solids, respectively) and potential for miniaturized sensor deployment. These systems can support smallholder coffee producers in optimizing fermentation processes and ensuring consistent coffee quality.

Fermentation is a pivotal biochemical process also in the **production of tea**, where it fundamentally determines the final product's chemical profile, sensory attributes, and commercial value. The transformation of tea leaves during fermentation, especially the oxidation of polyphenolic compounds like catechins, significantly influences the color, flavor, and aroma of the tea. Tea varieties (i.e., green, partially fermented such as oolong, and fully fermented or black tea) are primarily distinguished by their degree of fermentation. In green tea, fermentation is arrested to

maintain high catechin levels and a fresh, vegetal taste. In contrast, black tea undergoes full fermentation, drastically reducing catechin content while increasing theaflavins and thearubigins, which contribute to its dark color and smooth flavor. Theanine, a non-proteinogenic amino acid responsible for tea umami taste, also varies significantly across fermentation levels. It tends to degrade during fermentation, making it a useful marker alongside catechins for monitoring the progression of tea oxidation (Chen et al., 2021). To determine the concentration of these compounds, the traditional methods used include spectrophotometry and HPLC, which demand chemical reagents and specialized analytical instruments. As consumer demand for consistent quality grows and production becomes more industrialized, NIR spectroscopy has gained prominence for monitoring tea fermentation in real-time at a cheaper cost (Chen et al., 2021; Wang et al., 2021).

Chen et al. (2021) analyzed 161 tea samples, including green, partially fermented, and black teas, using NIR spectroscopy. Modified PLSR (MPLSR) was used to quantify total catechins and theanine. The optimal models achieved R^2_p values of 0.94 for total catechins and 0.92 for theanine in calibration sets, with RPD values of 3.16 and 3.38, respectively, indicating good model predictability. The most informative wavelength regions corresponded to overtone absorptions of functional groups characteristic of catechins and theanine, including combinations of C–H, N–H, and O–H bonds.

Wang et al. (2021) explored the use of a smartphone-based miniature NIR spectrometer combined with a computer vision system to monitor key chemical components across all black tea processing stages (i.e., withering, rolling, fermentation, drying). Using middle-level data fusion and PLSR, the Authors achieved RMSEP values of 0.66 ± 0.12 g/100 g and 1.06 ± 0.11 g/100 g and RPD values of 5.41 and 4.03 for polyphenols and catechins, respectively, indicating high model accuracy for quality control. Data fusion enabled improved performance compared with single-sensor systems.

NIR spectroscopy offers several important advantages for monitoring fermentation of plant products. As a non-destructive and rapid analytical technique, it allows real-time assessment of fermentation progress without damaging the samples. When integrated with chemometric approaches, it achieves high predictive accuracy by extracting meaningful chemical information from complex spectral data. Its versatility extends across various plant products and processing stages, supporting the au-

tomation of processing workflows and enhancing quality assurance by enabling consistent monitoring and control of fermentation-related parameters.

Kombucha is typically produced by fermenting sweetened tea with yeast and probiotic microorganisms. Monitoring total sugar consumption during fermentation is essential for controlling thallus growth and optimizing the process. However, sugar content is influenced by multiple variables, making its quantification challenging under standard conditions. Conventional analytical methods, such as HPLC, enzymatic assays, and the anthrone-sulfuric acid method, are commonly used for sugar detection, but they involve offline sampling, which is labor-intensive and poses contamination risks. Recently, NIR spectroscopy has gained attention for real-time monitoring of kombucha production (Zhao et al., 2023). For instance, Zhao et al. (2023) evaluated the application of NIR spectroscopy in kombucha fermentation, comparing PLSR, backpropagation artificial neural networks (BPANN), and hybrid PLS-BPANN models for predicting residual sugar content. Their findings revealed that non-linear models significantly outperformed traditional linear methods, with the PLS-BPANN model achieving a R^2_p of 0.9437 and a RMSEP of 0.8600 g/L. These results underscored the feasibility of integrating spectral data and AI-based algorithms for online monitoring with high accuracy. Building on this, Zhao et al. (2025) introduced a DL-enhanced vis-NIR calibration model for monitoring residual sugar and bacterial concentration in kombucha. Using CNNs (1DCNN and 2DCNN) combined with optimized feature reconstruction techniques, the study demonstrated improved predictive capacity and robustness, particularly with the 2DCNN model, which achieved RPD values of 4.49 and 6.88 for sugar and bacterial concentration, respectively. This approach provided a scalable, non-destructive solution for real-time process tracking.

In the production of **vinegar**, both alcoholic and acetic fermentation are important. Menozzi et al. (2024) conducted a comprehensive study to evaluate the application of FT-NIR spectroscopy for monitoring both the fermentation stages in red grape must during vinegar production. The dual fermentation process (i.e., alcoholic fermentation by *Saccharomyces cerevisiae* and subsequent acetic oxidation by *Acetobacter spp.*) was observed up to four months for two grape must batches (Ancellotta and Lambrusco blends) under surface fermentation conditions. FT-NIR spectroscopy effectively tracked fermentation kinetics, accurately predicting both ethanol content and total acidity throughout the entire fermentation

cycle. PLSR models based on the full spectral range (12,500–4000 cm^{-1}) yielded high predictive performance ($R^2_p > 0.98$ for both analytes). Models built using a reduced range (10,526–6060 cm^{-1}) also performed well, demonstrating the feasibility of employing affordable, miniaturized detectors. Thus, NIR spectroscopy presents several important benefits in the context of alcoholic and acetic fermentation monitoring. One of its principal advantages is its non-invasive nature, allowing for real-time, in situ analysis without disrupting the fermentation process. This technique is also capable of simultaneously predicting multiple chemical parameters, including ethanol, sugars, organic acids, and polyphenolic compounds, making it highly versatile. Moreover, NIR spectroscopy can lead to significant cost savings by reducing the need for labor-intensive procedures and consumable materials commonly associated with traditional analytical methods. Its adaptability further enhances its appeal, as portable and affordable NIR devices can be readily implemented in both laboratory and industrial production settings.

4.2 Limitations and challenges

The application of NIR spectroscopy as a tool for food fermentation monitoring in the PAT frame, while promising, faces several significant challenges and limitations that must be addressed to fully realize its industrial potential. Strengths, weaknesses, opportunities, and threats are summarized in the SWOT matrix of Fig. 3.

A primary limitation lies in the complexity of calibration. Building robust and reliable predictive models requires the collection of large, diverse, and high-quality calibration datasets that adequately represent the full range of process and product variability. This requirement can be particularly challenging in artisanal or small-batch fermentations, where sampling is limited and batch-to-batch heterogeneity is high. Without sufficient data diversity, models may lack the generalizability needed for practical application (Cavallini et al., 2025; Lin & Sun, 2020; Mehra et al., 2022; Zhou et al., 2024).

Environmental factors introduce another layer of variability. Spectral readings are sensitive to external conditions such as ambient light, sample temperature, turbidity, and optical path length. These sources of environmental noise can degrade spectral quality and measurement repeatability, reducing the reliability of models across different production setups. Furthermore, the high water content common in fermentation matri-

STRENGTHS ✓ Simultaneous quantification of multiple compounds (e.g., sugars, acids, polyphenols, alcohol). ✓ Non-destructive and rapid analysis allows real-time monitoring without sample disruption. ✓ Enables inline integration and process automation in both industrial and artisanal settings. ✓ Compatible with multivariate analysis and AI/ML models for predictive modeling. ✓ Supports sustainable practices through reduced reagent use and energy savings. ✓ Proven performance across diverse fermentations (e.g., beer, dairy products, tea, wine, kombucha).	WEAKNESSES ➢ High calibration complexity requires large, representative datasets. ➢ Sensitive to environmental noise such as temperature, light, and turbidity. ➢ Spectral collinearity complicates model interpretation and requires preprocessing. ➢ Limited interpretability of DL models poses challenges in regulated environments. ➢ Lower resolution of miniaturized devices may reduce analytical precision. ➢ Lack of intrinsic chemical specificity without chemometric models.
OPPORTUNITIES ✓ Growing demand for automation and traceability in fermentation-driven industries ✓ Development of portable, low-cost sensors using MEMS and fiber-optic technologies. ✓ Expansion to small-scale and home fermenters through user-friendly apps and tools. ✓ Integration with digital twins for predictive process control and anomaly detection. ✓ XAI integration to enhance transparency and regulatory acceptance. ✓ Wider application in personalized nutrition and functional foods..	THREATS ➢ Resistance from traditional producers due to cost or technical barriers. ➢ Need for frequent recalibration and maintenance of prediction models. ➢ Model transferability issues across different instruments or environments. ➢ Data privacy and compliance concerns in AI-powered process monitoring. ➢ Potential overreliance on AI models without expert validation. ➢ Regulatory hurdles related to black-box model deployment.

Fig. 3 SWOT matrix of the application of NIR spectroscopy as a PAT tool for food fermentation monitoring.

ces exacerbates these issues, as the strong absorption bands of water can obscure critical spectral features associated with target analytes (Gorla et al., 2023; Naito et al., 2024).

Spectral complexity also poses a significant challenge. NIR spectra are characterized by broad and overlapping absorbance bands, which introduce collinearity among variables and hinder the direct interpretation of raw spectral data. This multicollinearity necessitates the use of advanced preprocessing techniques as well as dimensionality reduction tools or variable selection methods. These approaches are essential for improving model robustness and reducing noise, but they also increase computational complexity and demand a high level of expertise (Gorla et al., 2023; Lin & Sun, 2020; Mehra et al., 2022).

The problem of model transferability further complicates the deployment of NIR systems. Models calibrated on one instrument, matrix, or environmental condition often underperform when applied in different contexts. Differences in sensor design, spectral resolution, and operating environments limit the generalization of these models, necessitating the

use of domain adaptation or transfer learning techniques to improve cross-platform robustness (Alfieri et al., 2025; Hassoun et al., 2024; Menozzi et al., 2024).

Moreover, while data-driven modeling, including the use of DL architectures, can enhance predictive performance, these models often suffer from limited interpretability. Their "black-box" nature presents challenges in regulatory contexts where transparent model behavior and validation are required. As such, clear documentation of model development processes and thorough validation protocols remain critical for ensuring their acceptance in industrial and food safety applications (Gunning & Aha, 2019; Hassoun et al., 2024). In a few food sectors NIR spectroscopy is recognized as a standard analytical method, and mainly for raw material or final product quality control. However, different guidelines for NIR applications have been published, setting the basis of good practices in sampling and spectra acquisition, together with ML performance evaluation (Squeo, Cruz, De Angelis, Caponio, & Amigo, 2024), which could be transferred to fermentation monitoring applications.

In summary, while NIR spectroscopy offers transformative potential for monitoring fermentation processes in food production, its successful application depends on overcoming challenges related to calibration complexity, spectral collinearity, environmental sensitivity, model transferability, and interpretability. Addressing these issues requires a multidisciplinary approach that combines robust experimental design, advanced AI tools, and transparent model governance.



5. Conclusions and future perspectives

Fermentation is one of the most versatile and impactful technologies in the food sector. Its capacity to preserve, enrich, and transform foods is incomparable. From enhancing food safety and nutrition to enabling sustainable production systems and novel functional foods, fermentation addresses many of the modern food system challenges. In traditional contexts, fermentation represents culinary heritage, nutritional resilience, and cultural identity. In industrial applications, it is the engine behind probiotics, functional ingredients, and sustainable food solutions. Innovations in bioprocess engineering, digital technologies, and synthetic biology continue to expand the possibilities of fermentation, making it a

frontier for future food innovations. Fermentation is actually entering a new era of digitally empowered production, where data-driven insights, predictive modeling, and sustainable practices converge. The convergence of advanced sensors, AI, and PAT is transforming fermentation into a highly intelligent and sustainable process. Despite technical and economic hurdles, these innovations offer solutions for consistent quality, scalability, and traceability in fermented food production.

In particular, NIR spectroscopy is rapidly transforming from a laboratory technique to a cornerstone of real-time fermentation monitoring. Its synergy with PAT marks a pivotal shift toward intelligent, data-driven food fermentation. These tools are being redefined by innovation in optics, computing, and AI, paving the way for more responsive, precise, and affordable fermentation control across scales and substrates.

Emerging developments in micro-electro-mechanical systems (MEMS) and fiber-optic technologies are enabling the creation of compact, portable NIR spectrometers. These miniaturized devices are not only rugged and low-cost but also suitable for in-line integration, allowing continuous, non-destructive monitoring of fermentation processes directly within bioreactors or production lines. This shift marks a transition from lab-based analysis to real-time, on-site data acquisition, enhancing responsiveness and reducing reliance on time-intensive sampling protocols (Ma, Liu, Liu, Wang, & Zhang, 2024).

The convergence of NIR spectroscopy with AI-driven process modeling and digital twins presents an opportunity to transform fermentation into a data-rich, self-optimizing system. Digital twins can use real-time spectral inputs from NIR to simulate and predict process evolution. Combined with ML, this approach enables predictive control, early anomaly detection, and optimized decision-making, paving the way toward closed-loop control architectures and adaptive fermentation ecosystems (Udugama et al., 2023; Zhang et al., 2025). Such systems represent a shift from passive monitoring to active process management, increasing yield consistency and product quality while reducing human intervention. AI algorithms, including ANNs, use data science and analytical science to solve a variety of optimization issues related to the multifaceted, interconnected, and nonlinear process of microbial fermentation.

The integration of XAI into NIR modeling is crucial for improving transparency and trust, particularly in regulated industries. Tools like SHAP values and saliency maps allow stakeholders to visualize the spectral feature driving model predictions (Gunning & Aha, 2019). This

transparency not only enhances regulatory acceptance but also supports quality assurance teams in validating model logic and refining operational strategies.

As NIR devices become more affordable and user-friendly, their applications are expanding to artisanal producers and home fermenters. Small-scale producers can now access real-time, professional-grade quality monitoring tools that were once exclusive to industrial facilities. This could catalyze innovation in craft fermentation, functional foods, and personalized probiotic formulations, contributing to broader food system resilience and innovation.

Together, these strategies lay the foundation for next-generation fermentation that is not only efficient and safe, but also tailored, functional, and sustainable.

References

- Abass, T., Eruaga, M.A., Itua, E.O., & Bature, J.T. (2024). Advancing food safety through IoT: Real-time monitoring and control systems. *International Medical Science Research Journal*, 4, 276–283. doi:10.51594/imsrj.v4i3.919.
- Abbaspour, N. (2024). Fermentation's pivotal role in shaping the future of plant-based foods: An integrative review of fermentation processes and their impact on sensory and health benefits. *Applied Food Research*, 4, 100468. doi:10.1016/j.afres.2024.100468.
- Adeleke, I., Nwulu, N., & Adebo, O.A. (2023). Internet of Things (IoT) in the food fermentation process: A bibliometric review. *Journal of Food Processing Engineering*, 46, e14321. doi:10.1111/jfpe.14321.
- Aguirre-Garcia, Y.L., Nery-Flores, S.D., Campos-Muzquiz, L.G., Flores-Gallegos, A.C., Palomo-Ligas, L., Ascacio-Valdés, J.A., ... Rodríguez-Herrera, R. (2024). Lactic acid fermentation in the food industry and bio-preservation of food. *Fermentation*, 10, 168. doi:10.3390/fermentation10030168.
- Alasi, S.O., Sanusi, M.S., Sunmonu, M.O., Odewole, M.M., & Adepoju, A.L. (2024). Exploring recent developments in novel technologies and AI integration for plant-based protein functionality: A review. *Journal of Agriculture and Food Research*, 15, 101036. doi:10.1016/j.jafr.2024.101036.
- Albino, M., Gargalo, C.L., Nadal-Rey, G., Albæk, M.O., Krühne, U., & Gernaey, K.V. (2024). Hybrid modeling for on-line fermentation optimization and scale-up: A review. *Processes*, 12, 1635. doi:10.3390/pr12081635.
- Alfieri, G., Riggi, R., Modesti, M., Bellincontro, A., Renzia, F., & Aleixandre-Tudo, J.L. (2025). Feasibility assessment of a low-cost near-infrared spectroscopy-based prototype for monitoring polyphenol extraction in fermenting musts. *Journal of the Science of Food and Agriculture*. doi:10.1002/jsfa.14321.
- Anumudu, C.K., Miri, T., & Onyeaka, H. (2024). Multifunctional applications of lactic acid bacteria: Enhancing safety, quality, and nutritional value in foods and fermented beverages. *Foods*, 13, 3714. doi:10.3390/foods13233714.
- Areti, H.A., Muleta, M.D., Abo, L.D., Hamda, A.S., Adugna, A.A., Edae, I.T., ... Gudeta, R.L. (2024). Innovative uses of agricultural by-products in the food and beverage

- sector: A review. *Food Chemistry Advances*, 5, 100838. doi:10.1016/j.focha.2024.100838.
- Bockisch, A., Kielhorn, E., Neubauer, P., & Junne, S. (2019). Process analytical technologies to monitor the liquid phase of anaerobic cultures. *Process Biochemistry*, 76, 1–10. doi:10.1016/j.procbio.2018.10.005.
- Castro-Reigía, D., García, I., Sanllorente, S., Sarabia, L.A., Amigo, J.M., & Ortiz, M.C. (2024). Bread fermentation monitoring through NIR spectroscopy and PLS-DA. Determining the optimal fermentation point in bread doughs. *Journal of Food Engineering*, 361, 111738. doi:10.1016/j.jfoodeng.2023.111738.
- Cavallini, N., Cavallini, E., & Savorani, F. (2025). Monitoring the homemade fermentation of readymade malt extract using the SCiO NIR sensor: A convergence of technology and tradition. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, 325, 125126. doi:10.1016/j.saa.2024.125126.
- Chang, X., Huang, X., Xu, W., Tian, X., Wang, C., Wang, L., & Yu, S. (2021). Monitoring of dough fermentation during Chinese steamed bread processing by near-infrared spectroscopy combined with spectra selection and supervised learning algorithm. *Journal of Food Process Engineering*, 44, e13783. doi:10.1111/jfpe.13783.
- Chen, S., Wang, C.-Y., Tsai, C.-Y., Yang, I.-C., Luo, S.-J., & Chuang, Y.-K. (2021). Fermentation quality evaluation of tea by estimating total catechins and theanine using near-infrared spectroscopy. *Vibrational Spectroscopy*, 115, 103278. doi:10.1016/j.vibspec.2021.103278.
- Cozzolino, D., Damberg, R.G., Janik, L., Cynkar, W.U., & Gishen, M. (2006). Analysis of grapes and wine by near infrared spectroscopy. *Journal of Near Infrared Spectroscopy*, 14, 279–289. doi:10.1255/jnirs.679.
- Dissanayake, I.H., Tabassum, W., Alsherbiny, M., Chang, D., Li, C.G., & Bhuyan, D.J. (2025). Lactic acid bacterial fermentation as a biotransformation strategy to enhance the bioavailability of phenolic antioxidants in fruits and vegetables: A comprehensive review. *Food Research International*, 209, 116283. doi:10.1016/j.foodres.2025.116283.
- Ferrer, A. (2007). Multivariate statistical process control based on principal component analysis (MSPC-PCA): Some reflections and a case study in an antibody assembly process. *Quality Engineering*, 19, 311–325. doi:10.1080/08982110701621304.
- Gallego-Martínez, J.J., Cañete-Carmona, E., Gersnoviez, A., Brox, M., Sánchez-Gil, J.J., Martín-Fernández, C., & Moreno, J. (2024). Devices for monitoring oenological processes: A review. *Measurement*, 235, 114922. doi:10.1016/j.measurement.2024.114922.
- Gänzle, M.G., Monnin, L., Zheng, J., Zhang, L., Coton, M., Sicard, D., & Walter, J. (2024). Starter culture development and innovation for novel fermented foods. *Annual Review of Food Science and Technology*, 15, 211–239. doi:10.1146/annurev-food-072023-034207.
- González-Mohino, A., Pérez-Palacios, T., Antequera, T., Ruiz-Carrascal, J., Olegario, L.S., & Grassi, S. (2020). Monitoring the processing of dry fermented sausages with a portable NIRS device. *Foods*, 9, 1294. doi:10.3390/foods9091294.
- Gorla, G., Ferrer, A., & Giussani, B. (2023). Process understanding and monitoring: A glimpse into data strategies for miniaturized NIR spectrometers. *Analytica Chimica Acta*, 1281, 341902. doi:10.1016/j.aca.2023.341902.
- Grassi, S., & Alamprese, C. (2018). Advances in NIR spectroscopy applied to process analytical technology in food industries. *Current Opinion in Food Science*, 22, 17–21.

doi:10.1016/j.cofs.2017.12.008.

Grassi, S., Alamprese, C., Bono, V., Casiraghi, E., & Amigo, J.M. (2014). Modelling milk lactic acid fermentation using multivariate curve resolution-alternating least squares (MCR-ALS). *Food and Bioprocess Technology*, 7, 1819–1829. doi:10.1007/s11947-013-1189-2.

Grassi, S., Alamprese, C., Bono, V., Picozzi, C., Foschino, R., & Casiraghi, E. (2013). Monitoring of lactic acid fermentation process using FT-NIR spectroscopy. *Journal of Near Infrared Spectroscopy*, 21, 417–425. doi:10.1255/jnirs.1058.

Gunning, D., & Aha, D.W. (2019). DARPA's explainable artificial intelligence (XAI) program. *AI Magazine*, 40(2), 44–58. doi:10.1609/aimag.v40i2.2850.

Harris, N., Gonzalez Viejo, C., Zhang, J., Pang, A., Hernandez-Brenes, C., & Fuentes, S. (2024). Enhancing beer authentication, quality, and control assessment using non-invasive spectroscopy through bottle and machine learning modeling. *Journal of Food Science*, 90, e17670. doi:10.1111/1750-3841.17670.

Hassoun, A., Dankar, I., Bhat, Z., & Bouzembrak, Y. (2024). Unveiling the relationship between food unit operations and food industry 4.0: A short review. *Heliyon*, 10, e39388. doi:10.1016/j.heliyon.2024.e39388.

Herrera-Ruiz, J.F., Fontalvo, J., & Prado-Rubio, O.A. (2024). Advances on hybrid modelling for bioprocesses engineering: Insights into research trends and future directions from a bibliometric approach. *Results in Engineering*, 24, 103548. doi:10.1016/j.rineng.2024.103548.

Izah, S.C., Odubo, T.C., Ogwu, M.C., & Hait, M. (2024). Aspects of microorganisms in the food industry. In Ogwu, M.C., Izah, S.C., & Ntuli, N.R. (Eds.), *Food safety and quality in the global south* (pp. 399–425). Singapore: Springer. https://doi.org/10.1007/978-981-97-2428-4_13.

Jang, H.J., Lee, N.-K., & Paik, H.-D. (2024). Overview of dairy-based products with probiotics: Fermented or non-fermented milk drink. *Food Science of Animal Resources*, 44, 255–268. doi:10.5851/kosfa.2023.e83.

Jaumot, J., De Juan, A., & Tauler, R. (2015). MCR-ALS GUI 2.0: New features and applications. *Chemometrics and Intelligent Laboratory Systems*, 140, 1–12. doi:10.1016/j.chemolab.2014.10.003.

Jiang, Q., Bao, Y., Ma, T., Tsuchikawa, S., Inagaki, T., Wang, H., & Jiang, H. (2025). Intelligent monitoring of post-processing characteristics in 3D-printed food products: A focus on fermentation process of starch-gluten mixture using NIR and multivariate analysis. *Journal of Food Engineering*, 388, 112357. doi:10.1016/j.jfoodeng.2024.112357.

Kasemsumran, S., Boondaeng, A., Ngowsuan, K., Jungtheerapanich, S., Apiwatanapiwat, W., Janchai, P., ... Vaithanomsat, P. (2022). Simultaneous monitoring of the evolution of chemical parameters in the fermentation process of pineapple fruit wine using the liquid probe for near-infrared coupled with chemometrics. *Foods*, 11, 377. doi:10.3390/foods11030377.

Khan, F., Khan, S.A., Sharma, G., Vishvakarma, R., Farooqui, A., Siddiqui, M.H., & Vimal, A. (2024). Introduction to bioprocess technology. In Dhagat, S., Jujjavarapu, S.E., Kumar, N.S.S., & Mahapatra, C. (Eds.), *Recent advances in bioprocess engineering and bioreactor design* (pp. 1–23). Singapore: Springer. https://doi.org/10.1007/978-981-97-1451-3_1.

Kumar, N.S.V., Meghana, I.S., Pavani, P., Kumar, N.S.S., & Chintagunta, A.D. (2024). Role of nanotechnology and Artificial Intelligence (AI) in waste management. In

- Dhagat, S., Jujjavarapu, S.E., Kumar, N.S.S., & Mahapatra, C. (Eds.), Recent advances in bioprocess engineering and bioreactor design (pp. 263–286). Singapore: Springer. https://doi.org/10.1007/978-981-97-1451-3_12.
- Kumar, N., Heena, Dixit, A., Mehra, M., Daniloski, D., & Trajkovska Petkoska, A. (2023). Utilization of whey: Sustainable trends and future developments. In Poonia, A., & Trajkovska Petkoska, A. (Eds.), Whey valorization (pp. 47–62). Singapore: Springer. https://doi.org/10.1007/978-981-99-5459-9_3.
- Lima, T.T.M., De Dea Lindner, J., & Martin, J.G.P. (2024). Sourdough bread market perception in Brazil: First insights. In Martin, J.G.P., De Dea Lindner, J., de Melo Pereira, G.V., & Ray, R.C. (Eds.), Trending topics on fermented foods (pp. 325–339). Cham: Springer. https://doi.org/10.1007/978-3-031-72000-0_12.
- Lin, X., & Sun, D.-W. (2020). Recent developments in vibrational spectroscopic techniques for tea quality and safety analyses. Trends in Food Science & Technology, 104, 163–176. doi:10.1016/j.tifs.2020.06.009.
- Littarru, E., Modesti, M., Alfieri, G., Pettinelli, S., Floridia, G., Bellincontro, A., ... Brizzolara, S. (2023). Optimizing the winemaking process: NIR spectroscopy and e-nose analysis for the online monitoring of fermentation. Journal of the Science of Food and Agriculture, 105, 1465–1475. doi:10.1002/jsfa.13336.
- Lopez-Palestino, A., Gomez-Vargas, R., Suarez-Quiroz, M., Gonzalez-Rios, O., Hernandez-Estrada, Z.J., Castellanos-Onorio, O.P., ... Figueroa-Hernandez, C.Y. (2025). Probiotic potential of lactic acid bacteria and yeast isolated from cocoa and coffee bean fermentation: A review. Fermentation, 11, 95. doi:10.3390/fermentation11020095.
- Ma, Y., Liu, W., Liu, X., Wang, N., & Zhang, H. (2024). Review of sensing and actuation technologies – from optical MEMS and nanophotonics to photonic nanosystems. International Journal of Optomechatronics, 18, 2342279. doi:10.1080/15599612.2024.2342279.
- Mehra, R., Kumar, H., Rafiq, S., Kumar, N., Buttar, H.S., Leicht, K., ... Korzeniowska, M. (2022). Enhancing yogurt products' ingredients: Preservation strategies, processing conditions, analytical detection methods, and therapeutic delivery – an overview. PeerJ, 10, e14177. doi:10.7717/peerj.14177.
- Menozzi, C., Foca, G., Calvini, R., Catellani, L., Bezecchi, A., & Ulrici, A. (2024). Comparison of different spectral ranges to monitor alcoholic and acetic fermentation of red grape must using FT-NIR spectroscopy and PLS regression. Food Analytical Methods, 17, 1171–1182. doi:10.1007/s12161-024-02636-3.
- Muncan, J., Tei, K., & Tsenkova, R. Real-time monitoring of yogurt fermentation process by aquaphotonics near-infrared spectroscopy. Sensors, 21, p. 177. <https://doi.org/10.3390/s21010177>.
- Naito, H., Doi, R., Maruyama, H., Wada, A., Morio, Y., & Murakami, K. (2024). Rapid measurement of sake mash using differential near-infrared spectra of diffuse transmission and transreflectance. Journal of Bioscience and Bioengineering, 137, 274–280. doi:10.1016/j.jbiosc.2024.01.009.
- Narayana, S., Christensen, L., Skov, T., & van den Berg, F. (2019). Mid-infrared spectroscopy and multivariate analysis to characterize *Lactobacillus acidophilus* fermentation processes. Applied Spectroscopy, 73, 1087–1098. doi:10.1177/0003702819848486.
- Niyigaba, T., Küçükgöz, K., Kołozyn-Krajewska, D., Królikowski, T., & Trzaskowska, M. (2025). Advances in fermentation technology: A focus on health and safety. Applied Sciences, 15, 3001. doi:10.3390/app15063001.

- Ogwu, M.C., & Ogunsola, O.A. (2024). Physicochemical methods of food preservation to ensure food safety and quality. In Ogwu, M.C., Izah, S.C., & Ntuli, N.R. (Eds.), *Food safety and quality in the global south* (pp. 263–298). Singapore: Springer. https://doi.org/10.1007/978-981-97-2428-4_9.
- Olatunde, O.O., Bandara, N., Coker, O.J., Ajayi, F.F., Ademola, O.M., Akinmosin, B.O., ... Fadimu, G.J. (2023). Novel food processing techniques and application for fermented foods. In Adebo, O.A., Chinma, C.E., Obadina, A.O., Soares, A.G., Panda, S.K., & Gan, R.-Y. (Eds.), *Indigenous fermented foods for the tropics* (pp. 467–481). Academic Press. <https://doi.org/10.1016/B978-0-323-98341-9.00010-4>.
- Oliveri, P. (2017). Class-modelling in food analytical chemistry: Development, sampling, optimisation and validation issues—a tutorial. *Analytica Chimica Acta*, 982, 9–19. doi:10.1016/j.aca.2017.05.013.
- Paramithiotis, S., & Ray, R.C. (2024). Recent concerns about fermented food safety. In Martin, J.G.P., De Dea Lindner, J., de Melo Pereira, G.V., & Ray, R.C. (Eds.), *Trending topics on fermented foods* (pp. 387–413). Cham: Springer. https://doi.org/10.1007/978-3-031-72000-0_15.
- Peng, M., & Liang, Z. (2020). Degeneration of industrial bacteria caused by genetic instability. *World Journal of Microbiology and Biotechnology*, 36, 119. doi:10.1007/s11274-020-02901-7.
- Pinto, A., Deryck, A., Lima, G.V., de Oliveira, A.C., Moura, F.G., Barbin, D.F., ... Rogez, H. (2024). Advances in the individual authentication of cocoa beans: Vis/NIR spectroscopy as a tool to distinguish fermented from unfermented beans and classify genotypes in the eastern Amazonia. *Food Control*, 164, 110559. doi:10.1016/j.foodcont.2024.110559.
- Ray, R.C., Paramithiotis, S., Thekkangil, A., Nethravathy, V., Rai, A.K., & Martin, J.G.P. (2024). Food fermentation and its relevance in the human history. In Martin, J.G.P., De Dea Lindner, J., de Melo Pereira, G.V., & Ray, R.C. (Eds.), *Trending topics on fermented foods* (pp. 1–57). Cham: Springer. https://doi.org/10.1007/978-3-031-72000-0_1.
- Salas-Millán, J.Á., & Aguayo, E. (2024). Fermentation for revalorisation of fruit and vegetable by-products: A sustainable approach towards minimising food loss and waste. *Foods*, 13, 3680. doi:10.3390/foods13223680.
- Sarma, U., Chatterjee, A., & Shrestha, R. (2024). Fermented food production in the bioeconomy context. In Martin, J.G.P., De Dea Lindner, J., de Melo Pereira, G.V., & Ray, R.C. (Eds.), *Trending topics on fermented foods* (pp. 59–84). Cham: Springer. https://doi.org/10.1007/978-3-031-72000-0_2.
- Schorn-García, D., Ezenarro, J., Busto, O., Aceña, L., Boqué, R., Mestres, M., & Giussani, B. (2024). A new index to detect process deviations using IR spectroscopy and chemometrics process tools. *Food and Bioprocess Technology*, 17, 2782–2792. doi:10.1007/s11947-023-03266-z.
- Squeo, G., Cruz, J., De Angelis, D., Caponio, F., & Amigo, J.M. (2024). Considerations about the gap between research in near infrared spectroscopy and official methods and recommendations of analysis in foods. *Current Opinion in Food Science*, 59, 101203. doi:10.1016/j.cofs.2024.101203.
- Stegmayer, M.A., Sirini, N.E., Ruiz, M.J., Soto, L.P., Zbrun, M.V., Lorenzo, J.M., ... Frizzo, L.S. (2023). Effects of lactic acid bacteria and coagulase-negative staphylococci on dry-fermented sausage quality and safety: Systematic review and meta-analysis. *Meat Science*, 206, 109337. doi:10.1016/j.meatsci.2023.109337.

- Tirado-Kulieva, V., Quijano-Jara, C., Avila-George, H., & Castro, W. (2024). Predicting the evolution of pH and total soluble solids during coffee fermentation using near-infrared spectroscopy coupled with chemometrics. *Current Research in Food Science*, 9, 100788. doi:10.1016/j.crfs.2024.100788.
- Udugama, I.A., Kelton, W., & Bayer, C. (2023). Digital twins in food processing: A conceptual approach to developing multi-layer digital models. *Digital Chemical Engineering*, 7, 100087. doi:10.1016/j.dche.2023.100087.
- Wang, Y., Li, L., Liu, Y., Cui, Q., Ning, J., & Zhang, Z. (2021). Enhanced quality monitoring during black tea processing by the fusion of NIRS and computer vision. *Journal of Food Engineering*, 304, 110599. doi:10.1016/j.jfoodeng.2021.110599.
- Westad, F., & Marini, F. (2015). Validation of chemometric models—a tutorial. *Analytica Chimica Acta*, 893, 14–24. doi:10.1016/j.aca.2015.06.056.
- Zhang, Y., Zhu, X., Wang, N., Liu, X., Wang, L., & Ning, K. (2025). Synergy of traditional practices and modern technology: Advancing the understanding and applications of microbial resources and processes in fermented foods. *Trends in Food Science & Technology*, 157, 104891. doi:10.1016/j.tifs.2025.104891.
- Zhao, S., Adade, S.Y.-S.S., Wang, Z., Jiao, T., Ouyang, Q., Li, H., & Chen, Q. (2025). Deep learning and feature reconstruction assisted vis-NIR calibration method for on-line monitoring of key growth indicators during kombucha production. *Food Chemistry*, 463, 14141. doi:10.1016/j.foodchem.2024.141411.
- Zhao, S., Adade, S.Y.-S.S., Wang, Z., Wu, J., Jiao, T., Li, H., & Chen, Q. (2023). On-line monitoring of total sugar during kombucha fermentation process by near-infrared spectroscopy: Comparison of linear and non-linear multiple calibration methods. *Food Chemistry*, 423, 136208. doi:10.1016/j.foodchem.2023.136208.
- Zhou, X., Li, L., Zheng, J., Wu, J., Wen, L., Huang, M., ... Zong, X. (2024). Quantitative analysis of key components in Qingke beer brewing process by multispectral analysis combined with chemometrics. *Food Chemistry*, 436, 137739. doi:10.1016/j.foodchem.2023.137739.