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REVIEW

Machine Learning-Driven Optimization for Digital Transformation in Non-thermal Food Processing

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Abstract
Non-thermal food processing has opened up new space and has emerged as a promising alternative to conventional thermal methods of food processing. These foods meet the growing consumer demands for high-quality, convenient, and minimally processed foods. The idea of proposing a machine learning (ML) strategy for finding the optimum process parameters and kinetics in food processing applications is new and challenging, but this new innovative approach requires considerable scientific effort. This review presents the applications of ML in the optimization of non-thermal food processing technologies such as high-pressure processing (HPP), pulsed light (PL), ultrasound (US), pulsed electric fields (PEF), cold plasma (CP), and irradiation (IR). These technologies have exhibited conspicuous advantages with respect to microbial inactivation, preservation of food quality, and environmental sustainability. Integration of ML with non-thermal technologies will enable better control and monitor in real time and optimize critical parameters such as pressure, frequency, and treatment duration. While numerical models have conventionally been used successfully for process optimization, ML provides better adaptability by identification of complex nonlinear relationships in food systems for more accurate prediction and adjustment. The key takeaways of this paper lie in the ML-driven monitoring system, integrated sensors, and real-time data accumulation in response to enhancing process efficiency with dependency natures inherently presented by food matrices. Further development of ML models, apparatus collection, and intelligent systems is expected to yield non-thermal food processing methods with enhanced sustainability, safety, and quality.

Keywords Artificial intelligence · High-pressure processing · Pulsed light · Ultrasound · Pulsed electric fields · Cold plasma

Introduction

The traditional method of food processing is the most used method across the world because of its product stability, capacity to guarantee microbial stability, and ability to deactivate spoilage enzymes (Khan et al., 2022). However, heat treatment may induce numerous physicochemical changes under severe conditions that can generate a negative impact on the organoleptic properties, destroy heat-sensitive food vitamins, remove some bioactive compounds, and produce potentially harmful components (Wang et al., 2022a, 2022b, 2022c, 2022d). Thus, the demand for novel non-heat-based technologies is increasing, and non-thermal processing technologies are gradually replacing traditional processing technologies.

The attention of engineers and researchers has been attracted to non-thermal methods such as pulsed electric

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field (PEF), high-pressure processing (HPP), cold plasma, ultrasound, high voltage electric field (HVEF), irradiation, pulsed light (PL), which have escalated for their good quality "fresh-like" characteristics with minimal or no changes. These methods induce cell electroporation for solid foods and are chemical residue-free processing method which involves the application of increased pressure on the products to achieve shelf-stable products by microbial and enzymatic inactivation with minimal impact on the nutritional and chemical composition (Goraya et al., 2024; Guo et al., 2024; Pezo & Donsì, 2025). In addition, they have been used to inactivate several pathogenic and spoilage microorganisms both in vitro and in different foods while resulting in minimal influence on the quality attributes (Bayati et al., 2024). Although they affect the food processing and final quality of the products, to achieve better quality of the product and less energy consumption, the effective parameters such as field strength, treatment time, specific energy, pulse shape, pulse width, frequency, temperature, and voltage should be optimized (Goraya et al., 2024; Guo et al., 2024).

Mathematical modeling of the non-thermal processing is an interdisciplinary approach for optimization process that involves engineering background with chemistry, reaction kinetics, structural changes, predictive microbiology, and nutrition. The literature has presented the comprehensive and advanced mathematical analysis of various non-thermal processes for different food products such as meat and poultry (Hashemi et al., 2023), fresh fruit and vegetables (Mishra et al., 2024), dairy products (Kaushik et al., 2024), and soft drinks and beverages (Yang et al., 2024). An actual system can be described by mathematical equations that simplify the most relevant properties of that system, and its solutions are predicted according to the specified initial conditions. However, complex, non-linear interactions between ingredients and processing conditions, as well as variability in samples and environmental factors, can lead to inaccuracies and uncertainties in the mathematical model's predictions (Kumar et al., 2024a, 2024b, 2024c). Therefore, a method to handle complex, non-linear relationships and large datasets more effectively than traditional mathematical modeling and allowing for more accurate predictions and adaptive optimizations in dynamic and variable processing environments is required.

Artificial intelligence (AI) and machine learning (ML)-based modeling has the potential to model nonlinear complex processes associated with food processing. ML-based modeling can effectively predict process kinetics and optimize process parameters efficiently for ensuring better-quality products (Dhal & Kar, 2025; Khan et al., 2022). Dhal and Kar (2025) underscored that the integration of AI with emerging technologies such as the Internet of Things, blockchain, and AI-powered sensors enables proactive risk management, predictive analytics, and automated quality control. Taking into account the unique benefits of ML-based modeling strategies, many researchers have attempted to apply AI to non-thermal food processing operations (Evrendilek et al., 2022; Pan et al., 2024; Yıkmış et al., 2024). ML has been widely used to solve problems such as dimensional reduction, feature extraction, and model prediction. Furthermore, the literature has been revealed that the AI could optimize the voltage, clay percentage, and number of cathode–anode for HVEF (Robin et al., 2022); optimize the range of amplitudes, frequency, and power for US process (Abedi et al., 2024; Yıkmış et al., 2024); optimize the pressure level and exposure time for HPP (Pan et al., 2024; Qiu et al., 2017); and optimize field strength, specific energy, pulse width, and frequency for PEF (Evrendilek et al., 2022). Thus, ML is crucial for optimizing and predicting outcomes in non-thermal processing by enhancing precision, efficiency, and the ability to analyze complex datasets.

A number of reviews detailing the application of machine learning in food processing are available in the literature (Barthwal et al., 2024; Esmaeily et al., 2023; Hassoun et al., 2023). However, there is no review (to the best of our knowledge) exclusively focusing on potential of machine learning in to digitalize non-thermal processing in food industry. Therefore, the current review paper introduces the ML-based models to predict the quality of food products during various non-thermal processing as well as the optimization of effective parameters in each method. In addition, the application of high-tech equipment, including machine vision systems, spectral devices, and intelligent sensors to digitalize the non-thermal processes, is explained. This review encourages researchers to acquire data that are reliable, reproducible, and devoid of methodological challenges.

Non-thermal Processing Methods

High-Pressure Processing

HPP is a non-thermal food preservation technology which can be considered a clean treatment technology due to its low energy consumption and waste residue risk. Application of HPP technology was significant to microorganisms in various food products to maintain and extending food shelf-life, reduced microbial load without the thermal consequences (Qiu et al., 2017). HPP has merits such as high color stability, flavor, and texture, and maintains the microbiological quality and quality of seafood products although the high investment costs (50–75% higher) of this innovative technology remain a problem for the food industry (Goraya et al., 2024; Pezo & Donsì, 2025). As has been previously reported by researchers, various chemical components can be effectively preserved by HPP in various food products (Song et al.,2023; Nuygen et al., 2024; Sherman et al., 2024). However, functionality of

HPP can be more improved by optimizing the process parameters and considering the properties of the food system.

By optimizing pressure level, treatment time, and temperature, the HPP can be tailored to maximize microbial inactivation while maintaining or even enhancing the sensory and nutritional quality of food products. Zhu et al., (2022a, 2022b) applied 100–400 MPa at 10 °C for 15 min as HPP to investigate the effects of HPP on microbial, textural, and sensory properties of low-salt emulsified beef sausage. Although the overall results were satisfied, the sensory and textural properties of sausages worsened for HPP treatments ≥ 300 MPa. Further, Ferreira et al. (2023) tried to optimize the HPP for ready-to-eat meat. They considered 400–600 MPa and 180–480 s for pressure and treatment time. They claimed that the inactivation of the microorganism ranged from 0.99 to 4.12 UFC/g by increasing the pressure and time treatment. Although the effect of HPP on microbial inactivation depends on the process parameters, some factors such as initial temperature of the food, food matrix and composition, product size, and geometry indexes affect the desired outcomes in terms of safety, quality, and shelf life (Li et al., 2020; Nuygen et al., 2024). Thus, controlling HPP as it enables the precise prediction and optimization of process parameters to achieve desired food safety and quality outcomes efficiently is essential.

On-line control of HPP operation not only improves nutritional value but also optimizes the operational energy consumption. For this reason, novel technologies such as machine vision have been applied to collect a series of parameters texture and color of the food, with the goal of real monitoring and control food processing (Zhu et al., 2022a; Bhagya et al., 2022). AI algorithms can identify patterns and relationships that are not immediately apparent through traditional methods, enabling more accurate predictions of microbial inactivation and quality preservation (Nayak et al., 2020). Pezo and Donsì (2025) leveraged ML to create advanced predictive models for microbial inactivation during HPP. They underscored the study's significance in advancing the comprehension of high pressure homogenization (HPH) impact on microbial inactivation, thereby bolstering food safety and prolonging shelf-life. These technologies facilitate real-time monitoring and adaptive control of HPP parameters, leading to enhanced process efficiency, consistency, and safety. The implementation of AI results in improved product quality and higher consumer satisfaction while also contributing to more sustainable and cost-effective food processing practices (Bhagya et al., 2022); Barthwal et al., 2024). Therefore, to improve the acceptance, sensory quality, and preference of HPP, future development needs to focus on AI-driven monitoring.

Pulsed Light

PL has been considered a new non-thermal sterilization technology that has been presenting instantaneous pulses of intense light with microbial inactivation, taking mere seconds. Literature explored the efficacies of the PL technique employed in liquid products (Salazar-Zúñiga et al., 2023; Brito & Silva, 2024), semi-solid products (Takaki et al., 2021), and solid products (Guo et al., 2024) and have significantly been able to achieve microbial inactivation. PL becomes limited by its relatively shallow depth of penetration that only allows surface decontamination, which may leave internal pathogens in thick or opaque foods unaffected. In addition, Vargas-Ramella et al. (2021) managed to spot yet another limitation with regard to PL-worth mentioning. He stated high energy requirements implicate PL, given that this may promote undesired changes in sensory or nutritional quality of the treated food when the system is not optimized. Cassar et al. (2022) and Pihen et al. (2024) also documented that the presence of some food items with irregular surfaces might further compromise the effectiveness of the PL method by allowing for nonuniform exposure and incomplete microbial inactivation. Since this would allow for better control of depth of penetration, energy distribution, and treatment uniformity, the call has been made to optimize the parameters of PL when trying to mitigate its limitations in the food industry.

Numerical models and simulations have been applied to address these PL challenges by modeling light distribution, optimizing treatment protocols, assessing its impact on food safety and quality, and overcoming limitations in terms of penetration depth and uneven exposure (John and Ramaswamy, 2020; Preetha et al., 2023; Guo et al., 2024; Brito & Silva, 2024). Comparison of PL inactivation kinetics and modeling of *Escherichia coli*, *Clostridium sporogenes*, and *Geobacillus stearothermophilus* was done by John and Ramaswamy (2020). Log-linear and Weibull model have been applied to optimize the PL process for inactivation kinetics. Preetha et al. (2023) used Biphasic, Log linear plus tail, and Weibull models to increase the performance of PL treatment on inactivation kinetics of *Escherichia coli* in fruit juices. Literature emphasized that various critical parameters are suggested by several researchers which should be considered when designing the experiments to assess the suitability of PL, such as the number of pulses, transparency of the medium, distance from the flash lamp, and the depth of the samples. Establishment of standardized treatments and protocols in compliance with the legal requirements for specific food products with specific PL equipment would be required for successful applications of the PL process. However, considering all aforementioned parameters creates a limitation for numerical modeling.

ML can also give better flexibility than traditional mathematical modeling. Automatic learning of complex patterns from large data enables superior predictions and real-time adjustments in the light PL treatment process. While numerical modeling has the advantage of giving deterministic insight into known physical principles, ML reveals hidden correlations, and optimization of the treatment protocols is thus allowed even when the underlying dynamics are not well understood (Rowan, 2019).

Ultrasound

Ultrasound is the new technology deputed to the improvement of quality features in food products and surely much more harmless to the environment. US often improves the system's solubility, emulsifying characteristics, antioxidant features, digestibility, and sensory features (Taha et al., 2024). It has been reported that US could enhance positively the stability of the bioactive component, inactivate microorganisms, and enzymes of food products, as reviewed by Santos et al. (2024), Li et al. (2024), and Wang et al. (2025). The effectiveness of US is basically influenced by three parameters, namely, frequency, amplitude, and intensity, which define the extension of the cavitation effects responsible for microbial inactivation and quality preservation (Mohammed and Alqahtani, 2022; Kaushik et al., 2024). The limiting factors of practical importance identified that may cause non-uniform processing are US duration and physical properties of the food matrix, such as viscosity and composition. Thereby, the understanding of the parameters of US and its optimization is essential for process efficiency enhancement and to assure stable non-thermal food preservation.

Mohammed and Alqahtani (2022), Sanches et al. (2023), and Kaushik et al. (2024) mathematically modeled various bacteria and food characteristics for kinetics, which enabled the optimization of parameters in the US for enhanced microbial safety in food and agricultural products. For example, Kaushik et al. (2024) applied two linear and nonlinear models. The versatility of US in the dairy industry was discussed regarding the bacterial load reduction in milk and also presented a useful tool for response prediction and its validation through kinetic modeling of pathogens in milk. Similarly, Esua et al. (2022) applied nonlinear models to describe the relationship between bacterial inactivation and US parameters. However, numerical models providing an optimum about the US process rely on simplified assumptions and may be poor to characterize the complexion of a process accurately.

AI can further enhance the performance of the US process by analyzing large datasets to identify the optimal parameters, adaptively adjusting the protocols of treatments, and making more accurate predictions across a wide variety of food matrices (Lin et al., 2023). In this regard, Yıkmış et al. (2024) optimized the bioactive compounds and ultrasound parameters in US-treated gilaburu water. As they reported, the optimization of US by ML was led to the enhancement of bioactive compounds present in gilaburu juice by US, therefore improving its quality parameters. From the literature, AI positively optimized US parameters while preserving various bioactive components in those food products treated by US (Patra et al., 2022; Pusty et al., 2024; Yıkmış et al., 2024; Abedi et al., 2024). However, further research regarding dynamic analysis and real-time modification of conditions for demand variables to achieve maximum efficiency and consistency always using ML and AI in US processing has to be performed.

Pulsed and High Voltage Electric Field

PEF and HVEF technology offer several advantages in the food industry, such as shelf-life extension, nutrient retention, and quality preservation for various food products (Brito & Silva, 2024; Guo et al., 2024; Huang et al., 2025). Research on PEF and HVEF has mainly focused on its influence on enzyme activity, the inactivation of microorganisms, and the shelf-life of fresh fruit and vegetables (Dalvi-Isfahan et al., 2023), beverages and juices (Brito & Silva, 2024), meat and poultry (Guo et al., 2024), and sea foods (Kulawik et al., 2023). This accords with literature, where it has been pointed out that if PEF or HVEF treatments are not optimized, they might exhibit a lack of microbial inactivation due to non-uniform distribution of electric fields and irregular and less treatment intensity. Besides, poor settings of operating parameters can bring about degradation to sensitive nutrients and bioactive compounds in food (Kulawik et al., 2023; Brito & Silva, 2024; Guo et al., 2024; Nikzadfar et al., 2024; Luangapai & Siripatrawan, 2025). Thus, pulse duration, pulse frequency, number of pulses, and the time of treatment are effective parameters for PEF and HVEF, which should be heeded.

Many researchers and engineers have tried to optimize PEF and HVEF parameters by simulating the complex interactions between the electric field and food matrix under various conditions (Ziaiifar et al., 2024). Computational models have allowed researchers to predict the electric field distribution, the electric field strength induced, and effects resulting in microbial cells and food properties (Ziaiifar et al., 2024). The restriction will then be when numerical modeling of PEF optimization during food processing is involved, based on simplified assumptions and idealized conditions without considering the real complex and heterogeneous features of food matrices and their potential different responses to the electric field.

It has been suggested that ML has representatively provided an influential approach to the optimization of the PEF process through its enabling in investigating complex nonlinear relationships between input parameters and treatment outcomes (Cheng et al., 2025; Evrendilek et al., 2022; Robin et al., 2022). Cheng et al. (2025) investigated the effects of PEF treatment on the quality and structure of duck eggs during pickling, and a ML model was developed to predict the salt content utilizing the predictive abilities of ML models. These algorithms identify the optimal combination of electric field strength, pulse duration, and frequency in addition to other variables for maximum microbial inactivation per minimum loss of food quality by training the ML models on a vast quantity of experimental data.

Cold Plasma

CP technology was put into action in the case of food processing for the desirable surface decontamination of pathogens and spoilage microorganisms of fresh produce and minimally processed foods to maintain quality and extend shelf life (Bayati et al., 2024). CP has been reported to inactivate surface microorganisms of a wide range in food products through the formation of a number of reactive species, such as ozone, nitrogen oxides, and free radicals attacking cell membranes and DNA. However, CP depends upon the electrical discharge of the CP, which consists of a dielectric barrier, corona, pulse, and high-frequency discharges (Kulawik et al., 2023; Nikzadfar et al., 2024; Wang et al., 2022a, 2022b, 2022c, 2022d). Moreover, some CP process parameters such as duty cycle, treatment time, and voltage have greater effects on the performance of CP. Despite many advantages brought about by CP applications, this technology still faces quite a number of challenges, especially scaling up, which involves increasing productivity and treating foods in large formats.

Optimization and control of the effects of CP on nutritional quality and sensory quality are under ongoing investigation. Various studies have conducted a deeper understanding of the important role that mathematical modeling plays in the dynamics underlying extraction of bioactive compounds under CP treatment (Mendes-Oliveira et al., 2019; Arserim et al., 2021; Qian et al., 2022; Sivri, 2024). Mendes-Oliveira et al. (2019) focused on the application of modeling in the inactivation of *Bacillus subtilis* spores during CP sterilization and reported that modeling CP processing is a matter of great interest because it may provide accurate estimation of time and conditions required for a complete plasma-based sterilization process. In addition, Sivri et al. (2024) applied Peleg's model, the power law model, two-site kinetic model, and Elovic's model for assessment of extraction kinetics from black chokeberries enhanced by CP. These studies show that a kinetic model was able to give an appropriate fit to experimental data obtained from samples exposed to CP, which means the applied model duly describes the kinetics under the CP process. Further, Arserim et al. (2021) utilized an inactivation model that suggested a multiphysics-based numerical simulation model to predict the concentrations and distributions of the reactive species in the dielectric barrier discharge CP system for the ultimate optimization of the CP process. The complexity of accurately simulating heterogeneous interactions of reactive species across diverse food matrices, together with the variability in microbial resistance and surface topography, has so far limited numerical simulation and mathematical modeling for optimization of CP treatment in food processing. The applications were found in optimizing the CP treatment in food processing with the use of ML for improving the prediction of the efficacy of the treatment by analyzing big and complex data sets to find the optimal parameters for microbial inactivation and the preservation of the quality of food (Cui et al., 2023; Özdemir et al., 2023; Rashvand et al., 2023).

Irradiation

Food irradiation in food processing involves a process of exposing food to ionizing radiation, with the use of gamma rays, X-rays, or electron beams, serving to deplete noxious microorganisms and parasites and hence prolonging the shelf life by ensuring the safety of food. IR enables the delay in the ripening and sprouting of fruits and vegetables to be maintained together with nutritional value and also sensory qualities of food (Chaudhary et al., 2024). Various techniques included in IR methods consist of gamma, electron beam, and X-ray. IR systems have been selected based upon specific requirements in the food product targeted, especially relating to the depth of penetration and the nature of the microorganisms or the pests involved. Gamma rays have been utilized to reach deep penetrations so that bulk portions of food items could be sterilized. Similarly, X-ray IR systems provide deep penetration similar to rays but are rather flexible and besides do not require the use of radioactive materials. In contrast, electron beam IR systems use high-energy electrons for surface-level or shallow penetration and fit best for the treatment of thin-packed foods besides decontamination of surfaces (Chaudhary et al., 2024). In order for optimization of the performance of each abovementioned IR system, one has to take care about the dosage to be absorbed and time of exposure, linked to food composition and material of packaging.

Computational modeling has optimized the IR method to simulate dose distribution, penetration depth, and microbial inactivation kinetics, thus allowing for accurate adjustments of IR parameters that are aimed at improving food safety and quality while minimizing energy consumption and processing time. Singleton et al. (2020)

presented a simple mathematical modeling of the dosage of irradiation calculated for single log10 reduction, considering the possible resistance that may exist for some pathogens after exposure to gamma-irradiation. Furthermore, Ganguli et al. (2020) optimized the IR process parameters for degradation using the RSM method, taking into consideration the effect of pH, the dosage of graphene oxide nanomaterial, and contact time as the variable factors in influencing the IR process efficacy. In addition, they employed an ML method to increase its accuracy in optimization. The accuracy was increased by 2% more than by mathematical modeling. Although in the previous research it was not very significant about the accuracy of ML and the mathematical model, ML could perform dynamic learning from large and complex datasets for outcome predictions seeking optimality with higher accuracy and adaptability to variable types of food and conditions. Therefore, different researchers need to continue developing ML models for the optimization of the irradiation process in handling complex nonlinear relationships between variables. This has to be pursued against a background of improving predictive accuracy across diversities of food types for efficiency and specificity in IR protocols.

According to the literature, it can be claimed that applying different non-thermal methods is highly popular, and all scientists have searched for the optimization of these processes. In Table 1 are the effects of applying various non-thermal processing techniques comprising HPP, PL, US, CP, IR, and PEF on various food products in terms of microbial safety, nutrient preservation, and physicochemical properties. Examples of the enhancing effects of HPP on both microbial safety and nutrient retention can be seen in chicken meat and juices at optimal conditions of pressure and time (Szczepańska et al., 2022). On the other hand, it can degrade some bioactive compounds, such as polyphenols and vitamin C, in some products. PL treatment, while very promising in terms of retention of antioxidants and phenolic content in juices, at higher fluences can affect aromatic compounds (Wang et al., 2022a, 2022b, 2022c, 2022d). US treatments enhance the bioavailability of certain important nutrients and the vitamin C and total phenolic content in juices, although the anthocyanin content might be reduced after some time (Gomes et al., 2022). PEF, in a nutshell, just increases the excretion of bioactive compounds from plant-based food products. In that effect, it gives the food better nutritional qualities (Visockis et al., 2021). In general, these non-thermal technologies have the potential to provide a means for better food safety and nutrient retention balance, although with great variability based on AI development.

Machine Learning Approach

Support Vector Machine

SVM became important for optimization of process parameter prediction in microbial inactivation and quality retention. Nonthermal techniques were applied for preservation value without varying the nutritional value of the food using PEF (Rashvand et al., 2024), HPP (Srisuwan and Innet, (2024), US (Fan et al., 2022), and CP (Rashvand et al., 2023). Therefore, SVM is put into application for modeling and prediction of the effects of these processes on microbial inactivation, enzyme activity, and physicochemical properties of complex nonlinear data sets generated from these processes. The use of SVM aids in the optimization of conditions that offer maximum microbial safety with retained sensory and nutritional qualities, hence improving the overall nonthermal processing efficiency in general within the food industry (Srisuwan and Innet, (2024).

Combination of US technique and LS-SVM model provides an effective guidance for improving meat quality in Tan sheep, hence offering a new evaluation method for animals with superior carcass traits. Further studies should be performed in order to apply technologies like US for establishing higher predictive power models (Fan et al., 2022; Yu et al., 2025a, 2025b, 2025c). Yu et al., (2025a, 2025b, 2025c) investigated on a fast real-time monitor of rice grains infested with *Sitophilus oryzae* based on terahertz imaging combined with machine learning and SVM model was improved by 9.68% after first-order derivatives (1-st der) preprocessing. Also, Liao et al. (2016) developed a predictive model hybrid of LS-SVM combined with the improved fruit fly optimization algorithm was adopted to predict the ultrasonically-assisted extraction process. Using the produced LS-SVM model, higher accuracy was manifested regarding the prediction and optimization of ultrasound-assisted extraction of bioactive components with antioxidant activity (Liao et al., 2016). Hence, the LS-SVM model was more efficient in analysis and improvement in the extraction compared to RSM (Li et al., 2022). Similarly, Khursheed et al. (2022) performed the ultrasound-assisted extraction of protein from mosambi peel which was considered a novel source and optimized the process of extraction for maximum yield of protein using SVM and the GA. They further stated that SVM has difficulty handling high-dimensionality data sets and computational complexity, such as are provided by US, and that there was a potential problem with the model performance optimization, such as kernel and parameter selection, which can reduce accuracy in nonlinear relationship modeling of the effects induced by ultrasounds in food properties.

Table 1 Effect of different non-thermal processing on the food products

Process	Product	Treatment condition	Observation	Reason for AI	Reference
HPP	Cloudy apple juice	Pressures: 300–600 MPa, time: 5–15 min	The highest inactivation of polyphenol oxidase and peroxidize (26%) was observed at 600 MPa and statistical changes in the color parameters	Reduce pressure time and increase reliability	Szczepańska, et al., (2022)
	Apple and strawberry	300, 450, 600 MPa/5 min	Slight decrease was noted in the concentration of caffeic acid, gallic acid, and epicatechin. Concentration of quercetin and phloridzin remained unaffected	Maximize nutrient content and shelf life	Salazar-Orbea et al. (2023)
	Beef sausage	Pressures: 100–400 MPa, temperature: 10 °C, time: 15 min	HPP at 100–200 MPa could reduce TVCs, TVBN, and cooking loss; increase protein solubility; improve several texture parameters (hardness, cohesiveness, chewiness); and maintain color	Improve texture and quality of food	Zhu et al., (2022a, 2022b)
	Concord grape juice	200–400 MPa, 40 °C, 1 min	Treatment at 400 MPa/40 °C/1 min (HPP-200–400) maintained the flavonoids and vitamin C concentration of HPP-200	Reduce energy consumption and cost	Li & Padilla-Zakour (2024)
	Pumpkin, butternut, peas, beetroot, purple potato purees	600 MPa, 90 °C, 5 min	Vit C content reduced by 3–14% in all the five selected purees. Vitamin C of 14% was observed to be higher for pumpkin	Raise accuracy and efficiency	Al-Ghamdi et al. (2020)
	Pomegranate juice	100 and 150 MPa, 42 and 46 °C	There is no significant reduction in AA content at pressure levels studied However, pressure of 150 MPa resulted in slightly lower AA values than at 100 MPa	Increase the nutrient content and quality of product	Benjamin and Gamrasni (2020)
	Sugarcane juice	523 MPa, 50 °C, 11 min	Improved physicochemical properties and decreased enzymes and microbes	Evaluate processing efficiency and improve accuracy	Sreedevi et al. (2021)
	Milk	100, 300, and 600 MPa, 40 and 80 °C, 2 min, number of pulses from 1 to 3 at 100 MPa	The rise in pressure up to 300 MPa promoted the disruption of the cell membranes of milk The solubility of the proteins increased by increasing the number of pulses from 1 to 3 at 100 MPa	Optimum number of pulses and pressure	Strieder et al. (2022)

Table 1 (continued)

Process	Product	Treatment condition	Observation	Reason for AI	Reference
PL	Apple carambola and black table grapes	3000 J·cm^{-2}, 90 °C, 5 min	The PL-treated juice preserved 61% more antioxidants, 38.8% more phenolics, and 68.2% more vitamin C	To optimize the dose of light energy and processing time	Basak et al. (2022)
	Orange juice	13, 40, and 66 J/cm^{-2}, 60 mL/min	The higher the fluence (66 J/cm^{-2}), the higher the *E coli* count reductions (2.6 log CFU/mL)	Maximize the storage time and quality of product	Preetha et al. (2023)
	Grape juice	Radiation distance: 2–8 cm, pulse numbers: 20–40 times, dilution ratio: 1–3	The contents of alcohols, esters, and aldehydes significantly decreased in aroma components, while the contents of ketones and acids significantly increased, alkanes were not affected	Optimize radiation distance and pulse numbers	Leran Wang et al., (2022a, 2022b, 2022c, 2022d)
	Yellow croaker	100, 200, 300, 400, and 500 J/pulse, 30 pulses	500 J/pulse PL treatment could lead to lipid oxidation and produce some other odors, but 300 J/pulse PL treatment could achieve the purpose of sterilization without affecting the quality of the yellow croaker	Optimize fluence range and pulse	Jianyou Zhang et al., (2022a, 2022b)
	Lime juice	312–761.4 J cm- 2.1, 2.4, 2.7 kV for 90 s	A reduction of > 5 log (microbial safety) in *E. coli*, AM, and M&Y after PL treatments at 761.4 J cm^{-2}	Raise accuracy and operation	Shaik and Chakraborty (2024)
	Carambola/black table grape	600 – 5000 J cm^{-2}	Molds and yields were below the detection limit at PL-fluences > 2400 J cm^{-2}, aerobic mesophilic at fluence of 5000 J cm^{-2} and coliforms at the lower fluence (600 J cm^{-2})	Improvement the level of PL-fluences	Chakraborty et al. (2022)
US	Guava juice	3300 W/L 2, 6, 10 min	19 and 17% increase in Vit. C and total phenolic content (TPC) of sonicated juice and increase their bioavailability	To optimize ultrasound frequency the and time and power	Kalsi et al. (2023)
	Citrus fruit pigmented oranges	400 W, 24 kHz, 5 min, 15 °C	The values of total phenolic content and DPPH of all citrus cultivars increased from 315.18 to 645.44 μgGAE/mL and 1001.5–1336.8 μmol/mL, respectively, after sonication	Optimize the frequency and increase reliability	Nadeem et al. (2022)

Table 1 (continued)

Process	Product	Treatment condition	Observation	Reason for AI	Reference
	Pumpkin juice	525, 975, and 1125 W, time: 5, 10, 12 min, temperature: 30–70 °C	A significantly high value (543.62 µg/mL) of total phenolic content in US-treated sample was observed as compared to CH (437.52 µg/mL). However, the increase in US treatment intensity reduced the DPPH activity	Decrease energy consumption and optimum temperature	Zhang et al. (2024)
	Cashew apple juice	500 W, 19 kHz, Time: 2–10 min, Temperature: 20, 40 °C	33% increase in total flavonoid content (TFC) at higher intensities. 57% increase in TPC at 20 °C for 10 min treatment. The total antioxidant activity showed an increasing trend in sonicated juice	Raise accuracy and reliability	Fonteles et al. (2021)
	Pomegranate juice	1200 W, 20 kHz 5, 12.5, 20 min	The optimized ultrasound treatment yielded 1678 mg GA/L of TPC and 72.31 mg C3G/L of total anthocyanin content	Reduced the processing time and energy	Bayati et al. (2021)
	Ready-to-eat blueberry	Low-frequency US (25 kHz, US-FC (2 min) alone. For US-PAA (1 min) + cold plasma (1 min)	The best disinfection efficacy of CP was observed at a pulse frequency of 400–800 Hz, and microbial reduction was positively correlated with plasma output power in the range of 50–800 Hz	Improve the efficiency	Wang and Wu (2022)
	Orange juice	19 kHz, energy densities of 9, 26, 43, 60, and 86 J/mL, 15, 45, 75, 105, and 150 s	There were not found differences for the ascorbic acid content between untreated orange juice and samples treated by ultrasound (9–86 J/mL)	Reduced energy consumption	Gomes et al. (2022)

Table 1 (continued)

Process	Product	Treatment condition	Observation	Reason for AI	Reference
PEF	Potatoes	Ultrasound frequency 20 kHz, 270 W, t 120 s with 30 s intervals, T: −0.5 °C	Multi-frequency ultrasonic treatment reduced the drip loss and firmness. Preserved the L-ascorbic acid content, total calcium content, and the total phenol content	Reduced the energy consumption	Zhu et al. (2020)
	Beet root	E: 0.5–2 kV/cm, t pulse duration: 100 µs, frequency: 1 Hz, specific energy input: 0.8–4 kJ/kg, pulse number: 1–100	Extraction of betalains was increased	To boost extraction and optimum the pulse duration	Visockis et al. (2021)
	Chicory	E: 150–900 kV/cm, pulse number: 100, train number: 10, 20, 40, inter-train pause: 2 min, pulse duration: 100 µs	Increase: juice yield (9%)	To decrease the energy consumption	Zhang et al., (2021a, 2021b)
HVEF	Ready-to-eat fresh salmon	Voltage ranging from 0 to 14 kV, time: 0, 6, and 15 min	HVEF did not significantly affect the compositions of amino acids or fatty acids in salmon, but a slight change in the contents of glutamate, saturated fatty acids, and monounsaturated fatty acids was observed	To improve the voltage range and time	Qi et al. (2022)
	Pomegranate fruit	Electric field levels: 0, 1.5, and 3 kV/cm	The total antioxidant content (total phenol content and ascorbic acid content) was increased significantly, and the levels of hydrogen peroxide in pomegranate fruit compared to control group were decreased	To upgrade better efficiency, optimize the electric field level	Lotfi et al. (2022)

Table 1 (continued)

Process	Product	Treatment condition	Observation	Reason for AI	Reference
CP	Grape	Voltage plasma: 60 kV, and time processing: 5, 10, 15 min	Increase in water diffusion speed while increasing process time Reactive plasma species degrade the hydrophobic epidermis, enabling better drying	To raise efficiency, optimize the voltage and time	Bao et al. (2020)
	Pea protein isolate	30 kV, time: 10 min	Gel forming parameters decreased to 70 °C/10–20 min from 95 °C/60 min	To reform time and frequency	Zhang et al., (2022a, 2022b)
	Soy protein	50 kV, 75 Hz, time: 180 s	Solubility, gelling, emulsion activity, emulsion stability, and foam capacity increased by 25, 13, 50, 110, and 25%	Increase reliability	Li et al. (2023)
	Pineapple juice	Power/voltage: 10, 15, 20 kV, frequency: 10, 15, 20 kHz, time: 1–9 min	Total phenols were increased	Maximize product shelf life	Porto et al. (2023)
	Coconut	Power/voltage: 18–28 kV, time: 1–3 min	TFA was increased and total phenols, ascorbic acid, and TSS were decreased	To optimize power or voltage and time	Chutia and Mahanta (2021)
	Kiwifruit juice	Sample amount: 20 mL, power/voltage: 20 kV 200, frequency: 700 Hz, 15 min	Decrease: glucose, increase: vitamin C	Maximizing the amount of vitamin C and maximizing glucose	Kumar et al., (2024a, 2024b, 2024c)
IR	Pear	UV-C irradiation of 0.12, 0.24, 0.36, 0.48, 0.72, and 1.08 kJ/m^2	The activities of chitinase, 3-glucanase (GLU), peroxidase, superoxide dismutase (SOD), catalase, phenylalanine ammonia-lyase (PAL), and the content of phenolic compounds in fruit were enhanced	To optimize the dose UV-C irradiation	Sun et al. (2022)
	Sweet cherry	Dose: 4 kJ m^{-2} or interactions of UVC with 2 regulated deficit irrigation (RDI)	Phenols were increased (21–36%)	To enhance the efficiency and the optimum dose to extend the product shelf life	Martínez-Hernández et al. (2020)
	Sweet cherries (*Prunus avium* L.)	Dose: 1.0–4.2 kJ m^{-2}	Induction of total phenolics, flavonoids, and anthocyanins (26%, 35%, and 76%, respectively)	Optimum the irradiation dose	Zhang et al., (2021a, 2021b)
	Fresh-cut watermelon	Dose: 1.6–7.2 kJ m^{-2}	Increase in antioxidant capacity (7%), maintenance of lycopene and ascorbic acid Microbial growth retardation. Only the lowest doses (1.6 and 2.8 kJ m^{-2}) preserved sensory attributes	Improve the capacity and efficiency	Artés-Hernández et al. (2021)

Also, the SVM can handle nonlinear complex relationships between cold plasma parameters and food safety outcomes with effective processing condition optimization. The in-packaged apricots were treated with dielectric barrier discharge (DBD) cold plasma, and prediction for the CO2 and ethylene production for the input parameters of the developed SVM regression intelligence models was done with developed SVM to achieve more accuracy (Rashvand et al., 2023). Further, the influence of PEF on drying kinetics during vacuum-assisted microwave drying of sliced apples was optimized by Rashvand et al. (2024). Some such kernel functions developed for nonlinear support vector regression (SVR) models were radial basis function, polynomial, Gaussian, and Pearson universal. They suggested that the challenge regarding the application of kernel functions of SVM to optimize the PEF processing was based on selecting the proper kernel that might encapsulate the complex nonlinear relations between PEF parameters, such as electric field strength and pulse duration and food quality or microbial inactivation outcomes. This will probably cause poor generalization of the model and result in suboptimal predictions, especially for different food matrices with varyingly diverse dielectric properties due to inappropriate choice of the kernel. The computation involved in tuning the kernel parameters of high-dimensional various non-thermal processing datasets complicates the optimization process and can make SVM unsuitable for scalability in food processing real-time process control (Rashvand et al., 2023; Srisuwan and Innet, 2024); Rashvand et al., 2024).

Decision Trees

Decision trees are a way of mapping out a decision, using a tree-like model for classification or prediction on input features. Each internal node in DT represents the choices made about any given attribute, and branches represent different possible outcomes (Khan et al., 2022). In non-thermal food processing, DTs keep their strength in simplicity and interoperability. They allow for easily modeling cause-effect relationships between process parameters and either food safety or quality outcomes. Compared to the other more complex methods, DTs are more interpretable and, hence, suitable for the optimization of non-thermal processes and understanding the interaction of each parameter with the final quality of food among other benefits (Ramirez-Asis et al., 2022; Wang et al., 2022a, 2022b, 2022c, 2022d).

DTs were used for process optimization in US due to its prowess in the provision of interpretable models that delineate specific ultrasound parameter-food quality attributes for informed decisions in process optimization (Abedi et al., 2024; Lin et al., 2023). In addition, for other non-thermal processing, cold plasma is effective with DTs. Cui et al. (2023) investigated a novel approach for the validation of plasma processing for decontamination. They indicated that there was a need to develop process validation since the species generated in plasma is complex as a function of conditions for plasma generation. Thus, gradient boosting decision tree was applied for data analysis to validate the effectiveness of decontamination by cold atmospheric pressure plasma and plasma-activated water. Literature showed that the normally applied DTs were susceptible to overfitting, especially on small or noisy datasets, leading to non-generalizing models on unseen data in nonthermal food processing optimization. Their tendency to construct overly simplistic models can also lead them to fail in capturing complex nonlinear relationships between parameters of processing and food quality outcomes, hence failing to capture important interactions that affect the efficacy of non-thermal methods (Ramirez-Asis et al., 2022). It is noticeable that only few literature can be found regarding the application of DTs for optimization of various non-thermal processing.

Random Forest

RF is a procedure whereby several decision trees are constructed based on their random subsets of data and features, and their predictions are merged to get better performance both in accuracy and generalization (Yu et al., 2025a, 2025b, 2025c). RF seems to be generally advantageous in optimization processes involving non-thermal food processing methods. As Sakai et al. (2023) and Xia et al. (2025) mentioned, it could model complex, maybe nonlinear relationships between process parameters and food safety or quality outcomes. On the other hand, RF is less prone to overfitting compared to SVM in that it can deal with noisy or incomplete datasets, characteristics of experimental food processing applications (Khan et al., 2022). This model will also be capable of ranking feature importance, aiding in the identification of critical process parameters that will enable the optimization of non-thermal technologies in an effective manner (Wang et al., 2022a, 2022b, 2022c, 2022d).

RF has been applied in US systems for food processing to model and predict the effects of ultrasound parameters, such as frequency and intensity. Samli et al. (2020) carried out on computer modeling of the enrichment process of sunflower and corn oils with olive leaves through ultrasound treatment. Using RF, they demonstrated that sunflower and corn oil were enriched in polyphenols by adding olive leaf extracts. Kunjiappan et al. (2024) maximized the extraction of bioactive ingredients from grape seeds using an ultrasound-aided extraction technique, and the validated extraction parameters were optimized and compared using the Adaptive Neuro-Fuzzy Inference System (ANFIS) and random forest (RF). The literature revealed that using RF in US systems had some difficulties such as handling large, high-dimensional datasets generated by complex US interactions, which can increase computational cost and model training time (Samli et al., 2020; Sakai et al., 2023).

PEF pre-treatment coupled with mechanical pressing, followed by water extraction, could provide an industrially relevant and sustainable alternative to produce value-added products from chicken meat using RF model to extract the feature importance, allowing identification of the more important parameters affecting the extraction of protein and carnosine (Robin et al., 2022). Özdemir et al. (2023) and Zhou et al., (2023a, 2023b) applied RF for optimizing the CP and IR processing, respectively. RF-based models were applied to predict the antimicrobial activity of the plasma-activated and IR liquids, which are structured on ensemble learning and trees, might have had superior performance to other models because of the data distribution. Overall, RF offers a versatile tool for data-driven decision making in various aspects of food processing, from quality control to consumer insights (Wang et al., 2022a, 2022b, 2022c, 2022d; Zhou et al., 2023a, 2023b).

Fuzzy Logic

Fuzzy logic is the computational approach to dealing with reasoning, which can be imprecise and approximate rather than fixed and exact by applying uncertainty and vagueness in the decision-making process (Jadhav et al., 2024; Zhang et al., 2025). In this respect, FL has been applied in the treatment of food where most of the optimization in the non-thermal methods is done using modeling based on complex relations among different types of inputs-pressure, temperature, and duration of treatments with consideration of the intrinsic variability in properties of foods and conditions of treatments (Ding et al., 2023). This approach makes control systems flexible enough to respond in view of changes in the real-time characteristics of food. Expert knowledge and subjective evaluation are combined in FL, enhancing process optimization—a huge factor to guarantee better preservation of foods along with retention of their quality without much loss concerning nutrition (Jadhav et al., 2024).

FL was applied in HPP to optimize treatment parameters by modeling and controlling the non-linear relationships between pressure, time, and food quality attributes (Kaushik et al., 2015). Sensory attributes of HPP mango pulp and litchi juice were evaluated and compared with untreated samples, and FL showed that HPP effect was dependent on product type and pressure. Also, Bose and Bhattacharjee (2018) developed a new equation in FL analysis for ascertaining the appropriate dose of gamma irradiation of virgin coconut oil. This new methodology of FL analysis could be used to rank samples rapidly and reliably, without any complexity of conventional similarity value approach. However, they reported that the challenge of using FL in HPP and IR of food lies in accurately defining the membership functions and rules needed to model the complex, which can be subjective and require extensive empirical data to validate.

FL demonstrated its ability to effectively manage and optimize other non-thermal processing such as cold plasma. Through FL, it was found that the sensory panelists judged the sample treated with cold plasma at 18.00 kV voltage for 1.75 min and blended with 1% orange to be more acceptable than the samples with higher concentrations of orange juice (Chutia et al., 2020). Kumar et al., (2024a, 2024b, 2024c) and Pipliya et al. (2024) used FL to optimize CP processing with respect to kiwifruit and pineapple juice, respectively, investigating its effect on physicochemical, nutritional, microstructure, and rheological properties and sensory attributes. Inherent in this intelligent system is the ability for adaptive control of those parameters with respect to the type of food, the desired level of microbial inactivation, and the quality attributes to be preserved due to the incorporation of fuzzy logic.

Genetic Algorithm

GA represents an evolutionary optimization technique that has proven to show good results while searching for optimum solutions to various bioprocesses. This approach has made it very possible to apply GAs in food processing optimizations so that big nonlinear problems of food processing can be solved by imitations of the process of natural selection. Food processing can be optimized according to various variables, and a few of them are temperature, time, ingredient ratios, or energy consumption. It works iteratively to evaluate the individual solutions, select the best ones out of those performing well, and generate a new candidate solution by crossover and mutation. This approach will enable the identification of near-optimal solutions with a view to improvement in product quality, improvement in efficiency, or reduction in production cost related to food processing industries (Nath et al., 2024).

Employing GA, the extraction optimization with pomegranate peels significantly contributed to the maximization of yield in terms of bioactive compounds, including polyphenols and antioxidants (Uca & Güleç, 2024). It has been compared with a great number of data analysis models as an optimization key for the US process (Rakshit & Srivastav, 2021; Yue et al., 2024). Further, this technique was integrated with other ML models so that the performance of GA could be enhanced in optimizing the US process (Khursheed et al., 2022; Pusty et al., 2024). For example, a technique like SVR-GA for optimization of protein extraction helped improve yields of proteins from mosambi peel powder based on US and extraction parameters like particle size, ultrasonic time, and amplitude (Khursheed et al., 2022). GAs should be able to enable food scientists and engineers to improve the efficiency of extraction processes, ensure high-quality products, and achieve a very efficient use of resources in food processing.

Researchers could also study the usage of GA in optimizing CP treatments in food industries as an effective way to improve food processing and optimize product quality for resource use. Kumar et al., (2023) and Pipliya et al. (2023) designed an algorithm using GA in determining the effect of dielectric barrier discharge non-thermal plasma treatment on physicochemical, nutritional, and phytochemical quality attributes of kiwifruit and pineapple juice, respectively. Although it yielded good results for GA in most optimizations of the non-thermal methods, some limitations take place while applying this technique to GA food processing optimization. Some of the major limitations include the increase in high computation complexity while dealing with multi-dimensional and nonlinear problems. Besides, they may increase the chance of premature convergence on local optima rather than global solutions. Hence, careful tuning of parameters is an important prerequisite for yielding robust and reliable results (Nayak et al., 2020; Khan et al., 2022). However, to achieve better accuracy, all of the aforementioned methods need preprocessing method.

Preprocessing methods like feature normalization (which is important to reduce data bias) and selection/ranking (which can also reduce the dimensionality of the dataset and concentrate the attention on the most informative variables) are indeed fundamental to increase the performance of machine learning techniques (Shi et al., 2024). Nayak et al. (2020) and El-Demerdash et al. (2022) claimed that straightforward preprocessing leads to better generalization, and it stabilizes the learning process in the sense that it prevents overfitting and leads to more reliable and more robust predictions in complex food processing as well as in monitoring situations.

Figure 1 illustrates a novel machine learning framework for sensory prediction and feature selection in food processing optimization. In this process, pre-processed input data of nine sensory attributes are normalized and split into training (70%) and testing (30%) for reliability of model. Feature selection is done dynamically based on rank algorithms, criteria for acceptance of new features being the improvement in the values of the main quality metrics (R^2 and RMSE). This adaptive feature selection guarantees that only the most informative predictors are

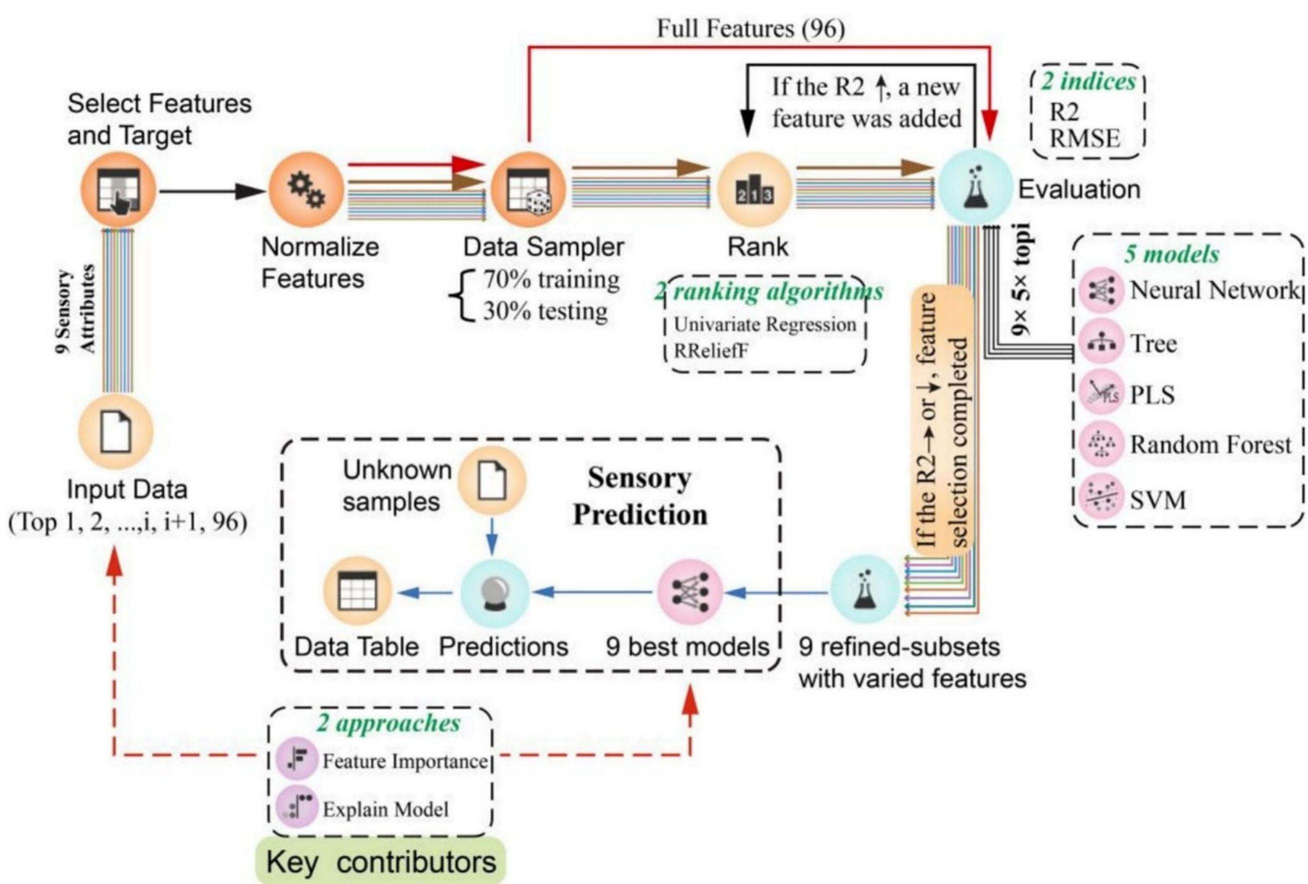

Fig. 1 Schematic representation of the machine learning-based framework for feature selection and sensory prediction (reproduced from Zhu et al. (2025))

included for model construction, preventing overfitting and enhancing the prediction performance. Five prediction models, neural networks, decision trees, partial least squares, random forest, and support vector machines, are implemented in the framework and systematically evaluated to discover the most effective models for different sets of features (Zhu et al., 2025).

Yıkmış et al. (2024) highlighted that feature importance analysis and model explainability tools further improve the interpretability of the results as the most relevant sensory contributors to product quality can be identified. Moreover, the literature (Rashvand et al., 2023; Wang et al., 2022a, 2022b, 2022c, 2022d; Xia et al., 2025) emphasized that such integration of predictive modeling with explainable AI is a considerable advance compared to conventional black-box methods and provides better scientific understanding and practical assistance to food engineers. It can be expected that through the design of an automated predictive model for unknown sample and online sensual quality determination, the intelligent, data-driven, and versatile non-thermal food technique could be developed based on the methods mentioned above. Overall, it is a best practice approach that promotes the accuracy and interpretability of machine learning analyses in food science.

Neural Network

Neural networks have been one of the widely used approaches in optimizing non-thermal food processing techniques. Those models can predict complex relationships of processing parameters by learning from experimental data (Ulu et al., 2025; Yu et al., 2025a, 2025b, 2025c). NN is particularly deserving in nonlinear multi-objective optimization problems which conventional models cannot solve and have the potential to enhance efficiency, safety, and product quality and reduce energy use while preserving sensory and nutritional properties. Indeed, Zhu et al. (2025) and Ma et al. (2024) reported that it is the adaptive learning that thus enables continuous process improvement as more data become available. NN excels over other ML models in handling large, complex datasets with high-dimensional features and non-linear relationships, making them particularly effective for predictive modeling in intricate systems. Their ability to automatically learn hierarchical feature representations without manual feature engineering provides superior performance in problems with unstructured data (Barthwal et al., 2024; Liu et al., 2023; Nath et al., 2024; Nayak et al., 2020).

Figure 2 shows a general structure of the NN, in which single nodes are known as artificial neurons. Each neuron is simply a classifier that generates an output signal in response to having been fed signals from earlier neurons (Shi et al., 2024). This flow of information between layers is aided by the transfer functions adopted during processing in a neural network, including a sigmoid, a linear transfer function, a hyperbolic tangent function, and a logistic function. In training, the network was exposed to input data for which there was already a known expected output; learning minimizes

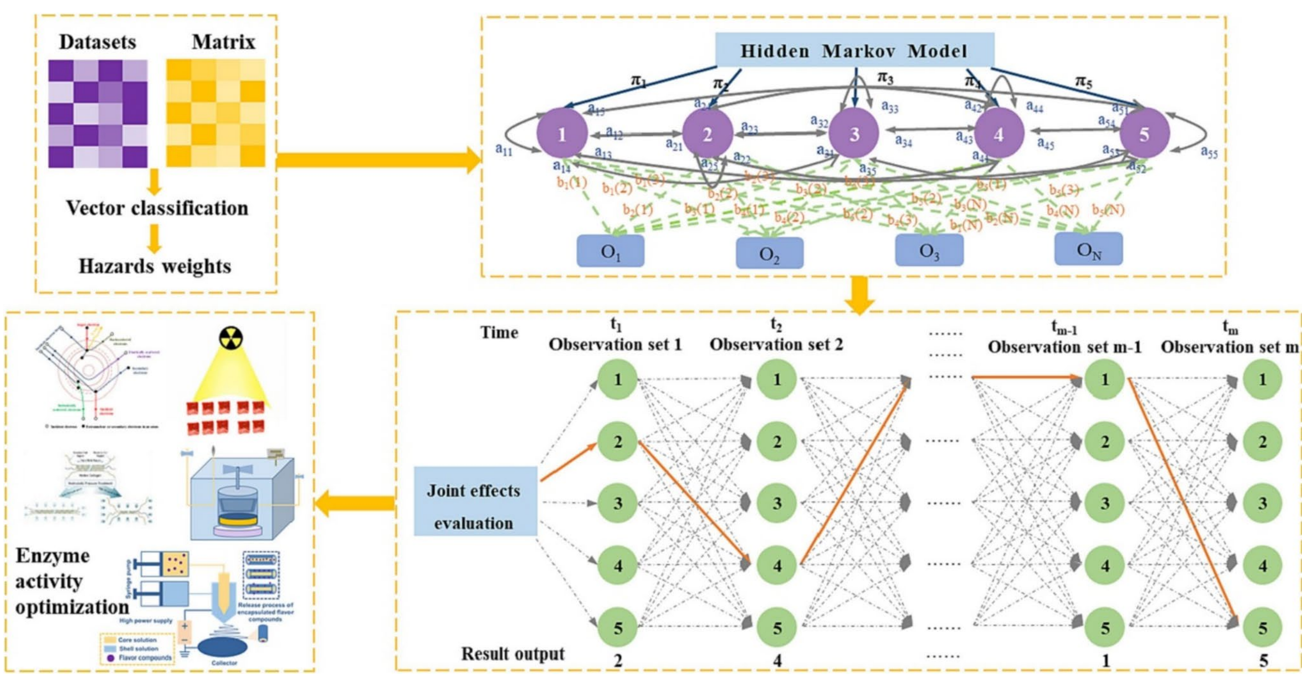

Fig. 2 Illustration of NNs structure and feedback control strategy based on multimodal data fusion (reproduced from Shi et al., 2024)

differences between what was predicted and what actually occurred. The backpropagation method was the most frequently used one for updating the weights and biases by propagating error back to minimize the loss function (Rashvand et al., 2023; Yıkmış et al., 2024). Then, researchers tried to investigate the optimal method and structure of NN for nonthermal treatment.

Determination of maximum output and efficiency requires optimization of the US extraction parameters. NN may be trained with a number of factors like frequency, intensity, time, and composition of solvent to obtain a preferred output of the extraction process (Rakshit & Srivastav, 2021). Optimization of process conditions for US treatment for bioactive components of tomato vinegar was carried out based on the NN model which had a superior prediction ability compared to the RSM model by Kashyap et al. (2021), Yıkmış et al. (2021), and Shekhar et al. (2023). NNs have demonstrated its potential to optimize US processing by accurately modeling the complex, non-linear interactions between ultrasound frequency, amplitude, and time. NNs could enhance process efficiency by predicting optimal operating conditions, minimizing trial-and-error experimentation, and improving product quality while preserving nutritional and sensory properties (Chen et al., 2023a, 2023b; Shekhar et al., 2023; Silva et al., 2024; Wang et al., 2024).

Artificial neural network (ANN) is a potent tool for active prediction and risk assessment associated with aflatoxins in the food industry. With this capability, food processors can strengthen the safety measurement of foods and reduce contamination to produce safe and quality food products. ANN model predicted the inactivation of aflatoxin-producing *A. parasiticus* and mitigation of aflatoxins in red pepper treated by PEF flakes by controlling factors or input variables such as frequency, treatment time, and energy instead of a statistical approach (Evrendilek et al., 2022). Many researchers developed ANN algorithms to model the process of extraction of various oil using PEF and determined that pre-treatment of PEF resulted in the production of the product with the desired efficiency and physicochemical properties (Lal et al., 2021; Razghandi et al., 2024; Zhao et al., 2022).

Also, NNs could analyze sensory data to detect quality attributes under HPP. Chakraborty et al. (2019) developed the inactivation trend of pectin methylesterase in pineapple puree during HPP combined ANN and kinetic approach. Further HPP parameters for not-from-concentrate combined peach and carrot juices, based on developed backpropagation neural network (BPNN) model for predicting antioxidant capacity was assessed by Liu et al., (2022a, 2022b). Comparing the traditional and some other ML methods, NN had several advantages for not only HPP but also other nonthermal processing such as CP which can help to predict treatment outcomes and enable real-time monitoring and control. Jaddu et al. (2022) and Zhou et al., (2023a, 2023b) combined ANN and GA in the food and juice industry to optimize CP processes and quality control, and they reported the integrated ANN could successfully analyze complex data patterns.

ANN exhibited specific advantages in non-thermal processing compared to other ML models. ANN proved very successful in modeling complex, nonlinear relationships during optimization processes with the involvement of multiple variables like ingredient interactions (Bhagya Raj & Dash, 2022a, 2022b). The high computational requirement and chances of overfitting in the event of small or noisy datasets, commonly faced in food processing conditions, are the major drawbacks of ANNs (Nayak et al., 2020; Zhu et al., 2025). Unlike simpler models like decision trees or linear regression, ANNs lack interpretability, making it difficult to understand how they derive predictions, which is crucial in food processing. Other models may offer faster training times and better generalization for smaller, structured datasets, making them more suitable for less complex tasks in the food industry (Ramirez-Asis et al., 2022; Khan et al., 2022; Chhetri, 2024).

From the literature, it can be noted that non-thermal processing has lately been optimized by applying the under-attack ML method. There is a lengthy application of different ML algorithms to optimize various food products (Table 2). For the wide application area in biological products and processes, SVM, GA, NN, and FL were used. For instance, Zhu et al. (2022a) and Khursheed et al. (2022) used SVMs with different kernel functions for the prediction of output based on various methods of treatment. NN-GA algorithms have been applied for increasing the extraction efficiencies of bioactive compounds from fruit peel-like persimmon (Giri et al. et al., 2024) and cranberry (Xue et al., 2021). In addition, higher predictive performances of NN models have been recorded in process optimization, namely, lipid synthesis and ultrasound-assisted olive oil bleaching by Asgari et al. (2017), proving in this way the strong application of NN for both prediction and optimization purposes in food science. Table 2 highlights the use of ML in yield improvement, process optimization, and enhancement of predictive accuracy in food systems in an effective manner.

Intelligent Devices

Applications of AI in the processing of non-thermal foods are effective but depend on the availability of data and the quality of data obtained. In this light, optimal equipment is necessary to obtain data accurately. The most commonly applied technologies in this area include the following: machine vision and sensors (Balkır et al., 2019). Machine vision systems employ cameras, image capture cards, and enhanced image processing technologies in data acquisition

Table 2 Applications of ML techniques in non-thermal food processing optimization

Applied ML	Tuning parameters	NT process	Product	Remarks	Reference
SVM	RBF kernel function, weight vector, bias value, error variable, regularization parameter	US	Tan sheep	The LSSVM nonlinear approach seemed to be a promising model for evaluating carcass traits and saleable products	Fan et al. (2022)
	Kernel function (radial basis function RBF), regularization parameter		*Euonymus alatus* (Thumb.)	Fruit fly optimization algorithm (IFOA)-LS-SVM model has a good prediction performance for the yield prediction of quercetin and rutin from Euonymus alatus (Thunb.) Sieb	Liao et al. (2016)
	-		Mosambi peel	Genetic algorithms can be successfully applied to maximize the extraction yield	Khursheed et al. (2022)
	Bias term, weight matrix, nonlinear function, kernel parameter, and the penalty parameters		Corn stalk	The optimum parameters for process pretreatment were as follows: weight of corn stalk 53 g, dual-frequency ultrasound, ultrasonic duration time 33 min, alkali pretreatment time 56 h	Dong and Chen (2019)
	Cost, gamma		*Agaricus bisporus* (mushroom)	Two partial least square regression (PLSR) and (SVM) full-band models using different preprocessing methods for predicting soluble solids content	Zhu et al. (2022a)
	C, γ, and the kernel function		Orange	The Pearson VII Universal Kernel (PUK)-based kernel SVM and the RBF kernel	Soltani Firouz et al. (2021)
	Non-linear transformation, kernel functions, kernel width, and the penalty coefficient	HPP	Mandarin juice	Optimum conditions for assessment of high pressure processed mandarin juice in the headspace by using electronic nose	Qiu et al. (2017)
	Kernel width and the penalty coefficient (0.01, 0.1, 1, 10, and 100)	CP	Apricot	The effects of CO2 and ethylene production on self-life of the apricots were analyzed by ANN and SVM	Rashvand et al. (2023)
	Kernel function, input vector, Lagrange multipliers, support value, bias term	IR	Shrimp	Compare the performance of two kinds of neural networks, and the LS-SVM model was proven to have better prediction abilities than BPNN	Xiong et al. (2016)

Table 2 (continued)

Applied ML	Tuning parameters	NT process	Product	Remarks	Reference
RF	Min samples split, max features, bootstrap	US	Apple	Compare the performance of six classes of sliced windfall apple samples and the values of 93%	Çetin et al. (2023)
	Min samples leaf, max depth		Milk	The nested cross-validation and the external validation set ($N=45$) indicated the RF model had the highest predicting accuracy of 97.8%	Huang et al. (2023)
	-	PEF	Chicken meat	PEF improved the extraction of anserine and carnosine by 7 to 53% compared to the control, depending on the process conditions, for 5- and 120-min incubation in water	Robin et al. (2022)
DT	Max features, max depth, bootstrap		Egg	Used the GINI index to select the optimal division points of the optimal features	Shi et al. (2022)

Table 2 (continued)

Applied ML	Tuning parameters	NT process	Product	Remarks	Reference
FL	Fuzzy rule base, fuzzification strategy	US	Rosa Canina-L seeds	Fuzzy data exhibited small deviation with satisfactory coefficient of determination ($R2 > 0.98$) that clearly proved very good performance of fuzzy-logic-based model in prediction of removal efficiency of Pb (II)	Javadian et al. (2018)
	Center of gravity, T-norm, error threshold		Gourd juice	An innovative approach of hybrid fuzzy logic and proportional odd modeling (FL-POM) was implemented for the analysis of the sensory scores	Das et al. (2022)
	Function type, structure of rules	CP	Blended beverage of TCW and orange juice	Through fuzzy logic, it was found that the sensory panelists judged the sample treated with cold plasma at 18.00 kV voltage for 1.75 min and blended with 1% orange to be more acceptable than the samples with higher concentrations of orange juice	Chutia et al. (2020)
	-		Pineapple juice	The fuzzy logic evaluation showed that optimized NTP-treated juice had superior sensory characteristics than extremely NTP- and thermally-treated juice	Pipliya et al. (2024)
	Value of membership function, mean value of the fuzzy number, membership function, time	IR	Virgin coconut oil	This new methodology of fuzzy logic analysis can be used to rank samples rapidly and reliably, without any complexity of conventional similarity value approach	Bose & Bhattacharjee, (2018)
GA	Number of variables, lower bound of variables, upper bound of variables	US	Sugarcane juice	The outcomes of the optimization study would facilitate suitable utilities of GA in other food process applications. In addition, the principal component analysis provided an overview of the interrelationships among quality parameters	Panigrahi et al. (2022)

Table 2 (continued)

Applied ML	Tuning parameters	NT process	Product	Remarks	Reference
	Population type, population size, population creation function		Persimmon fruit peel	The optimum condition of the extraction process according to the integrated ANN-GA model was found to be ultrasonication power of 230.176 W, extraction temperature of 50.661 °C, solid liquid ratio of 28.273 mL/g, and solvent concentration of 62.750% with fitness value of 3.087	Giri et al. (2024)
	Population selection function, crossover function, crossover probability, mutation function, number of generations, function tolerance		Red cabbage	The integrated ANFIS-GA model predicted the optimum values of process parameters at 252.114 W for ultrasonication power, 52.715 °C of temperature, 2.0677:1 of molar ration of DES	Kasturi Pusty et al. (2024)
	Crossover rate, bound of variables, crossover probability		The minerals from *Galium mollugo* L	Based on RSM-GA optimization, the optimum extraction temperatures for CE and USAE were found to be 80 8 C and 40 8 C, ensuring the highest yields of K, Ca, and Mg in 180 min and 80 min	Milić et al. (2017)
	Mutation rate, selection method, crossover operator		Pomegranate (*Punica granatum*) peel	By applying artificial neural network-multiobjective genetic algorithm, it was found that at optimum condition of 35 mL of solvent, 35% amplitude, 23 min, and 100% duty cycle	Rakshit et al. (2020)
	Population size, crossover function, crossover probability		Cranberry	The optimum extraction parameters to achieve the highest yield of anthocyanins (7.25 ± 0.02) mg/g	Xue et al. (2021)
	Membership function, population type, population size		Dragon fruit slices	The relative deviation between the experimental and integrated ANN-GA model predicted values for water loss, solid gain, and color change values under optimum conditions was less than 6.880%	Bhagya Raj & Dash (2022)
	Population creation function, crossover probability		Mosambi peel	The model accurately predicted both seen and unseen data ($R2$ = 0.9934 and 0.989)	Khursheed et al. (2022)
	Population type, number of generations, function tolerance		Apple bagasse	The coefficient of determination ($R2$) for every response was higher, and other statistical parameters were lower in ANN-GA	Patra et al. (2022)

Table 2 (continued)

Applied ML	Tuning parameters	NT process	Product	Remarks	Reference
	Lower bound of variables, upper bound of variables, mutation probability		Raspberry	The optimum extraction parameters to achieve the highest yields of anthocyanins at 1.378 ± 0.009 mg/g from raspberries via UADESE were obtained at a water content of 29%, ultrasonic power of 210 W, extraction temperature of 51 _C, and extraction time of 32 min	Xue et al. (2020)
	Selection method, crossover probability		Pomegranate pomaces	The ideal model process parameters were optimized to have a liquid–solid ratio of 49.0 mL/g, an ethanol concentration of 28 g/100 g, an ultrasonic time of 27 min, and an ultrasonic power of 330 W, with a maximum value of 86.98% for the anticipated ACN yield	Yue et al. (2024)
	-		Apple bagasse	The extraction of phenolic compounds from CAB using ultrasound treatment was significantly higher than the untreated CAB	Patra et al. (2021)
	Crossover function, crossover probability, mutation function, number of generations	CP	Coconut water (*Cocos nucifera* L.)	ANN/GA used for better prediction and optimization as compared with RSM	Chutia & Mahanta, (2021)
	Mutation rate, selection method, crossover operator, population size, crossover function, crossover probability		Kiwifruit juice	The optimum condition obtained from ANN-GA was 30 kV, 5 mm, and 6.7 min, respectively	Kumar et al., (2023)
	Population size, crossover rate, mutation rate, selection method		Pineapple juice	The ANN-GA approach produced the optimal condition, 38 kV, and 631 s and caused the inactivation of peroxidase (POD) and bromelain by 87.24% and 51.04%	Pipliya et al. (2023)

Table 2 (continued)

Applied ML	Tuning parameters	NT process	Product	Remarks	Reference
NN	Number of hidden layers, number of neurons in hidden layers, training function	US	Lipid	NN showed strong prediction and fitting ability ($R=0.9663$) and finally obtained the optimal synthesis scheme was catalyst concentration of 1.5 (w/w%), reaction time of 65 min, oil/methanol molar ratio of 1:5, and 50 ℃ reaction temperature	Liu et al., (2022a, 2022b)
	Batch size, number of epochs, algorithm function		Olive oil	ANN could precisely simulate ultrasound-assisted bleaching with high *R*2 (up to 90%) and low MSE within an ultrasonic bath	Asgari et al. (2017)
	Number of neurons in hidden layers, number of epochs		Garlic (*Allium sativum* L.)	Using ANN led to shorter extraction time, lower extraction temperature, less solvent used, and better recovery of investigated compounds	Ciric et al. (2020)
	Activation function, loss function, number of neurons in hidden layers		*Allium sativum* leaves	The optimum values of the independent variables obtained using ANN-GA were 60% ultrasound amplitude, 13 min treatment time, and 53% ethanol concentration, having applied energy of 26,150 J and calorimetric energy of 161.37 J	Shekhar et al. (2023)
	-		Meghalayan cherry fruit (*Prunus nepalensis*)	ANN could precisely simulate ultrasound-assisted bleaching with high *R*2 and low MSE within an ultrasonic bath	Kashyap et al. (2023)
	Number of hidden layers, number of neurons in hidden layers	HPP	Juice	A highly accurate BPNN model was developed for predicting antioxidant capacity, thus demonstrating that BPNN is a convenient and reliable prognostic tool for quality predictions	Liu et al., (2022a, 2022b)
	Number of neurons in hidden layers, number of epochs, activation function		Pineapple puree	The developed combined ANN-kinetic model be useful to design and select the high-pressure processing condition for pineapple puree targeting PME inactivation	Chakraborty et al. (2019)

Table 2 (continued)

Applied ML	Tuning parameters	NT process	Product	Remarks	Reference
	Batch size, number of epochs, training function	CP	Kodo millet flour	The result revealed ANN had superior model than RSM with good accuracy and better performance	Jaddu et al. (2022)
	Number of hidden layers, number of neurons in hidden layers, activation function, loss function		Haskap berries (*Lonicera caerulea* L.)	The ANN-GA was suitable for optimizing the CP by greatly improving the process yield and the utilization of biomass	Li et al. (2023)
	Number of hidden layers, number of neurons in hidden layers	IR	Smoked bacon	The application of artificial neural networks realized the prediction of total bacterial count and sensory quality of irradiated bacon	Qiu et al. (2017)
	Batch size, number of epochs, number of hidden layers, number of neurons in hidden layers	PEF	Red pepper flakes	The relationships between independent variables and explanatory variables can be determined empirically from data processing approach using machine learning and ANN instead of a statistical approach	Evrendilek et al. (2022)
	Number of neurons in hidden layers, number of epochs		Jackfruit waste	It was observed that the ANN was found to be more superior in execution than the Box-Behnken design model	Lal et al. (2021)

in the processing of non-thermal foods (Hou & Zhang, 2022). These systems automatize tasks that were conventionally performed by hand, hence enhancing efficiency and consistency. Machine vision has been found particularly effective in automating food inspection processes to attain high standards in the quality and safety of food. Also, sensors are pivotal in monitoring various parameters throughout the stages of non-thermal food processing. These are chemical and physical sensors and advanced nanotechnology-based sensors that monitor food quality by detecting contamination and tracing spoilage (Adetunji et al., 2022; Cozzolino, 2022).

Machine Vision

Machine vision systems utilize optical devices to identify food types, quality, defects, and impurities. These devices include hyperspectral cameras (Ren et al., 2020), imaging probes (Gocławski et al., 2017), infrared (IR) cameras (Cisneros-Carrillo et al., 2020), and digital cameras (Çetin et al., 2023). Such equipment is beneficial for observing modifications in food products treated by nonthermal processing methods. Machine vision facilitates the detection of nonthermal processed products. Distinguishing irradiated food products is a common application of machine vision systems. Despite the confirmed safety of irradiated products by international and national organizations, labeling irradiated food products is necessary for legal compliance and consumer transparency (Buczkowska et al., 2020). Cisneros-Carrillo et al. 2020) used an automated vision system (AVS) for the investigation of the optical absorption coefficient of laser irradiation in grains of corn. It was based on thermal analysis by infrared camera and photoacoustic spectroscopy with a monochromator and photoacoustic cell. The AVS implemented an integrated approach through image analysis, feature extraction, feature selection, and pattern recognition technique that correctly identified crystalline and floury corn grains. Further research into the feasibility of this approach using products of different colors and at different intensities of laser could be more indicative.

The assessment of food quality is necessary in non-thermal processed food products. More research on real-time detectors by the use of machine vision can hasten things in food distribution and related areas. Considered very vital, the preprocessing techniques, such as normalization, image transformation, and data augmentation, are employed to improve model performance. Improving the applicability of machine vision systems in continuous food industrial monitoring and quality control would be possibly enhanced by the development of a high-speed image acquisition system and the exploitation of advanced machine learning algorithms.

Miscellaneous Sensors

New view related to food safety, quality, and sustainability was opened by the integration of smart sensors, artificial intelligence, and big data optimization in non-thermal food processing. Sensors have excellent potential in terms of data intake by capturing diverse parameters. E-nose and E-tongue devices are significantly effective for the detection of non-thermal processed foods. One E-nose or an E-tongue consists of a single array of gas or chemical sensors designed separately to account for the human olfactory and gustatory systems, respectively. The E-noses will employ gas sensor arrays, whereas the E-tongues apply chemical sensor arrays for the detection of complex chemical and biological signatures. Qiu et al. (2017) assessed HP-processed mandarin juice using an E-nose. Data reduction through the Locality Preserving Projections (LPP) algorithm and classification algorithms such as SVM and extreme learning machine (ELM) enhanced the E-nose's diagnostic accuracy.

AI-based models for optimizing nonthermal processes—highly linked to nonthermal-assisted extraction—require collecting a high number of data from several parameters with a high level of accuracy (Shekhar et al., 2023). Sensors are a key point in developing reliable models of optimization. Among them, one of the most valued groups refers to spectrophotometers. It also measures the total phenol content (Kumar et al., 2023), total monomeric anthocyanins (Yue et al., 2024), total protein content (Robin et al., 2022), FTIR spectra (Kashyap et al., 2023), antioxidant activities (Patra et al., 2022), and bioactive ingredients (Kunjiappan et al., 2024). This increases precision and efficiency in AI-driven, non-thermal process optimization (Table 3).

Economic and Environmental Impact

ML has enhanced the sustainability of non-thermal food processing by making better use of energy, reducing waste, and enhancing efficiency (Wang et al., 2022a, 2022b, 2022c, 2022d). Non-thermal methods preserve the quality of food away from heating; operation complications may lead to resource wastage. Machine learning algorithms, in turn, enable the optimization of these processes by predicting the optimal conditions of operation, thereby reducing trial-and-error experiments and improving product consistency. According to Lin et al. (2023) and Khan et al. (2022), ML allows real-time monitoring so that any immediate adjustment of parameters can be made, which otherwise would result in overutilization of energy or resources. It helps for long-term sustainability with least resource input, ensuring safety and quality of food, hence reducing the environmental burden of traditional thermal methods of food processing.

Table 3 Applied equipment combined ML to optimize some non-thermal processing

Technique	Equipment	Model	Product	Objective	Observation	Reference
Machine vision	RGB camera	Multiscale shortcut convolutional neural network (MSCNN)	Rice	Identifying plasma-treated fine-grained rice growth	The model with three shortcuts achieved the highest precision	Chen et al., (2023a, 2023b)
	Visible-near-infrared reflectance HSI system	Spectral channels 3D attention module (C3DAM)—ResNet-based HSI data classification (HSI-3DResNet)	Rice	Plasma-treated rice recognition	C3DAM improved the recognition accuracy of the model to 97.47%	Tang et al. (2023)
	Magnetic resonance imaging (MRI)	CNN	Apple	Evaluating fluence (UV dose) distribution on apple surfaces	Finding a linear relationship between the color difference of RCF and Fluence	Cankal et al. (2023)
	Digital camera	Logistic model tree, random forest, Bayes net	Windfall apples	Distinguish dried apples with and without ultrasound pretreatment	The samples with and without ultrasound pretreatment classified with 95% accuracy using RF	Çetin et al. (2023)
	Multispectral imaging (MSI) system (405–970 nm)	Least squares-support vector machines (LS-SVM)	Shrimp	Discriminate irradiated shrimps at various irradiation doses	LS-SVM achieved prediction accuracy of 76% at 1 kGy, 90% at 4 kGy, and 100% at 10 kGy	Xiong et al. (2016)
Sensors	E-nose	Locality preserving projections (LPP)-SVM	Mandarin juice	Assess HP-processed mandarin juices at various pressures	LPP combined with SVM and ELM enhanced diagnostic accuracy	Qiu et al. (2017)
	H nuclear magnetic resonance (NMR)	PCA, CT	Beef	Discriminate between non-irradiated and irradiated beef at various doses (2.5, 4.5, 8 kGy)	Glycerol, lactic acid esters, and tyramine identified as biomarkers; classification trees effectively distinguished irradiated beef samples	Zanardi et al. (2015)
	Attenuated total reflection Fourier transform infrared (ATR-FTIR) spectroscopy	RF	Baijiu	Identify baijiu samples according to different irradiation doses (0, 4, 6, and 8 kGy)	RF model using 20 spectral markers achieved accurate identification	Zhou et al., (2023a, 2023b)

Incorporation of ML in non-thermal food processing could mean economic advantages. While the initial investment with ML infrastructure is high, such as for data collection, algorithm development, and computational resources, the long-term benefits that come along compensate for the cost involved in investment (Nayak et al., 2020). Simultaneously, by optimization of parameters in processes and reduction of food losses, ML decreases operational cost, in particular for power-consuming methods such as those based on HPP (Kaushik et al., 2015; Srisuwan and Innet, 2024 or PEF (Evrendilek et al., 2022; Lal et al., 2021; Razghandi et al., 2024). Besides that, by determining the quality of products more precisely, firms will avoid overproducing a product by maintaining inventories at strategic levels and avoiding returns resulting from spoilage. In addition, ML real-time monitoring eliminates much of the manual intervention and qualitative quality control testing, significantly lowering labor costs and further creating better efficiency on production lines (Chhetri, 2024; Khan et al., 2022).

Important environmental consequence of the usage of machine learning in non-thermal food processing is essentially through optimization of resources and reduction of wastes. Comparatively, the carbon footprint of just non-thermal processes themselves tends to be lower than that seen with traditional thermal processing, but further environmental impacts can be minimized by ML through enhanced process control. It can predict, for example, the necessary pressure or strength of an electric field to inactivate the microbes on-site and avoid overprocessing (Razghandi et al., 2024). Similarly, because ML reduces food spoilage by enhancement of predictive quality control, it also helps reduce food waste and, by implication, decreases the production of greenhouse gases that result from waste disposal (Wang et al., 2022a, 2022b, 2022c, 2022d). Another great advantage offered by the non-thermal process is reduced needs for chemical preservatives, thus accordingly satisfying the growing consumers' interest in cleaner and more sustainable ways of food production (Lin et al., 2023; Ramirez-Asis et al., 2022).

The integration of ML in non-thermal food processing for multifaceted development related to sustainability, economic effectiveness, and environmental protection all mean that by optimizing the processing condition, ML supports sustainability in food production by reducing waste. Economically, ML has contributed to cost savings by enhancing efficient processing and reducing labor and material costs (Evrendilek et al., 2022). The environmental benefits will be supporting the reduction of energy consumption and food waste in line with global goals related to carbon footprint reduction and using greener technologies (Razghandi et al., 2024). These benefits put together make ML an essential tool for non-thermal food processing that needs to move forward in a more sustainable, cost-effective, and greener direction.

Challenges and Future Work

Despite potential of ML in non-thermal food processing, there are a number of limitations. One major limitation is that ML requires a large amount of high-quality data to train accurate models. Since many of the non-thermal processes like US or CP are at a relatively nascent stage, quality datasets might not be available or tough to retrieve. Besides, most ML models easily get puzzled by the complex and variable nature of the biological material, such things as food, where small changes in the composition of the raw material can strongly influence the result. Then again, overfitting—especially in the case of dealing with databases of limited sizes or imbalanced datasets—can also steer models to poor performance in an industrial setting because of their good performance in a lab environment. Moreover, most ML models, specifically those of deep learning algorithms, are considered to be black box because the form of their decisions is impossible to provide insights about, which might be a problem for industries that demand regulatory transparency, such as food safety.

Various challenges exist in implementing ML in non-thermal food processing. Key among them is the complexity of integrating ML in food processing systems. The variables encompassed by non-thermal technologies are not always linear and easy to model. For this, sophisticated algorithms become necessary. Adaptation to ML tends to be expensive infrastructure changes, such as sensors for online data acquisition and connectivity that allows for remote monitoring and control, thus becoming a financial burden to the usual smaller food processors. There are also regulatory challenges; food safety regulations demand rigorous validation and transparency, yet ML models, particularly complex ones like neural networks, are often opaque. Ensuring that ML-driven processes meet regulatory standards for food safety and quality assurance is therefore difficult. Furthermore, there is a skills gap in the food industry, where many practitioners may not have the necessary expertise in ML, data science, or computational methods, posing challenges for widespread implementation.

For the future, ML in non-thermal food processing is very promising since continuous technological development can solve known limitations and challenges. Improved IoT integrations and better sensors enable better data collections, hence a better way to develop more accurate and generalizable ML models. Other emerging fields include explainable AI, which could enhance the interpretability and therefore the suitability of ML models for regulatory environments. Besides, increasing computational power and ease of access to cloud-based ML platforms will increasingly lower the threshold for smaller food processors. Integration with other enabling technologies, including robotics and automation, will also enable more real-time capability for ML systems, including autonomous control over non-thermal processing techniques. As the work continues to improve, ML might start to play an important role in precision food processing, unique parameters being applied to different batches, and even individual lots, in order to optimize efficiency and quality.

Although ML in non-thermal food processing has brilliant future prospects, some of the drawbacks to be overcome are related to data availability, model interpretability, and investment in considerable infrastructures. When these current obstacles have been surmounted through better data accrual, improved model explainability, and enhanced computational capabilities, wider-scale adoption can take place. One can well expect that with the advancement of technology, ML will be a mainstay in non-thermal food processing for its high efficiency, less wastage, and consistent quality of products. It will require continued research and development, complemented by collaboration with the industry, to realize all the advantages of machine learning in this innovative area.

Conclusion

This paper reviewed a number of non-thermal food processing technologies and focused on showing how their optimization can be done via machine learning models. Also, ML has been emphasized as critical for the optimization of those processes so as to provide real-time control with high precision/adaptability compared to conventional models. Similarly, the integration of machine vision systems, advanced sensors, and spectroscopic methods played a crucial role in the development of technologies of non-thermal food processing. These tools together create improvements in data collection, monitoring, and data analysis to enhance the quality and safety of food. Some of the limitations and challenges recorded are high computational demands from ML models and the large datasets required for proper training of such models. Furthermore, the complexity of the food systems and domain interactions within the food properties and parameters of non-thermal processing have always hindered the application of conventional numerical models. In the future, these technologies are likely to be further improved by ML-driven approaches, especially when methods of data collection improve. Future progress in the use of non-thermal processing within industry will require AI for real-time monitoring and the optimization of such processes, together with sensors. Indeed, such integration would facilitate the quest for efficient, sustainable, and high-quality food production practices.

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Declarations

Conflict of Interest The authors declare no competing interests.

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