ANNUAL REVIEWS

Annual Review of Food Science and Technology

Machine Learning in Automated Food Processing: A Mini Review

Lu Zhang, Remko M. Boom, and Yizhou Ma

Laboratory of Food Process Engineering, Wageningen University & Research, Wageningen, The Netherlands; email: remko.boom@wur.nl

Annu. Rev. Food Sci. Technol. 2025. 16:25–37

The *Annual Review of Food Science and Technology* is online at food.annualreviews.org

https://doi.org/10.1146/annurev-food-111523-122039

Keywords

Industry 4.0, machine learning, smart food manufacturing, automation, data-driven approach, food personalization

Abstract

Industrial food processing is rapidly transforming into automation and digitalization. Automated food processing systems adapt to variations in raw materials and product quality requirements. Implementing automated processing systems can potentially improve the sustainability of our food systems by improving productivity while reducing environmental impacts. Nevertheless, the adoption of automated food processing systems is still relatively low. In this review, we discuss the concept of automated food processing and summarize the recent advances in applications of machine learning technologies to enable automated food processing. Machine learning can find its applications in formulation development, process control, and product quality assessment. We share our vision on the potential of automated food processing systems to adapt to complex raw materials, mass customization, personalized nutrition, and human–machine interaction. Finally, we pinpoint relevant research questions and stress that future research on automated food processing requires multidisciplinary approaches.

1. INTRODUCTION

A new era of agri-food production called Agri-Food 4.0 has been emerging, with strong focuses on digitalization, automation, connectivity, and efficient and sustainable usage of natural resources (Miranda et al. 2019). Several representative technologies in this era include the Internet of Things (IoT) for connectivity, data science and machine learning for decision-making, automated robotic systems for flexible hardware design and manufacturing, and cloud computing for real-time data processing. "Automation," "intelligence," and "smart" therefore become keywords describing the modern development of food processing. Integrating automated processing in food production can improve productivity, efficiency, accuracy, and reliability, resulting in more consistent product quality with less waste and minimal risk of contamination via human contact (Gray & Davis 2013). Across the agri-food production chain, automated robotic systems or manipulators have been developed for agricultural production such as processing of raw meat, poultry, and fish; harvesting fruits and vegetables; and packing and palletizing finished food products (Chua et al. 2003).

Industrial food processing, as a critical step in the agri-food production chain, focuses on converting raw food ingredients into consumer products. Food processing has always been carried out with manufacturing equipment, which has become more automated over the years. Equipment or machinery in food processing systems such as a spray dryer or a pasteurizer is used in modern food factories to produce food products aiming to achieve standardized and consistent product quality at large scale. Industrial robotic systems such as manipulator-like articulated structures are employed in food factories to achieve preprogrammed, large-volume productions (Khan et al. 2018, 2022). Nevertheless, most of the current automation in food processing still focuses on high-throughput production of standardized products with limited variations. These systems lack adaptability to the variability and complexity of raw ingredients, product specifications, and personalized consumer needs. Although conventional automated robotic systems are often programmed in a deterministic fashion (i.e., rule-based programming), the design of automated food processing further requires independent decision-making and high adaptation to varying and new situations (e.g., new ingredients and processing condition drifts) during food processing. Inspired by the Agri-Food 4.0 paradigm, future food processing units should consist of (*a*) (semi)autonomous units that are equipped with sensors to monitor environmental and processing conditions, (*b*) a control unit to analyze signal data and make decisions (e.g., by using a machine learning approach), and (*c*) actuators to perform real-time actions. This type of operation paradigm (i.e., sensing, machine learning, and robotics) has been successfully adopted in the agriculture industry, such as in intelligent greenhouses, sun trackers, hexapod robots for field monitoring, agricultural drones, and harvesting robots (Miranda et al. 2019). However, this approach has not yet been implemented in automated food processing.

Innovations in automated food processing systems are demanded from two aspects. On one hand, food processing systems should be flexible and robust in handling process disturbances such as variability from raw materials (especially when plant-based ingredients are used). Raw materials used in food production can vary in composition, shape, color, and other material properties (e.g., rheological properties) (Kjetil Jørgensen 2004), which can impact the process itself and the final product. Even if the material properties of raw ingredients can be characterized in advance, our current understanding of their complex interactions with processing conditions and the quality of final products often remains empirical. Hence, simply automating repetitive operations does not suit the needs for automated food processing. Case-by-case adjustment and optimization of processing parameters are often necessary to manufacture food products with consistent quality and safety assurance. This is an ongoing effort in food manufacturing, which requires extensive expert experience, manual trial and error, and precise implementation of process control. On the other hand, the increasing demand for mass customization and personalization among consumers requires modern food manufacturing systems to be more flexible and intelligent. On-demand food production requires modern food processing techniques to quickly optimize processing conditions to adapt to specific consumer demands based on preferences and nutritional needs. Therefore, adaptive, interactive, and smart automated food processing systems can potentially overcome the challenges set by the variability of raw food ingredients and implement robust process optimization to manufacture food products that meet the needs of individual consumers.

This review aims to provide an overview of recent developments in machine learning applications for automated food processing and discuss relevant research topics that can further advance this field. We also provide a case study on the applications of machine learning and computer vision to optimize extrusion-based 3D food printing. In the literature survey, we specifically focus on the application of machine learning for food processing (i.e., manufacturing raw food materials into consumer products). The scope of food processing includes formulation development prior to processing, optimization, and control of unit operations during processing, and quality assessment of products after processing. Machine learning applications in primary food production, postharvesting (e.g., grading, classifying of fruits), and packaging and distribution of food products have been intensively reviewed and discussed elsewhere (Nayak et al. 2020, Zhu et al. 2021) and therefore are not included in this review.

2. MACHINE LEARNING FOR AUTOMATED FOOD PROCESSING

2.1. Automated Food Processing

Automation already plays an important role in modern farming and postharvesting to achieve tasks such as weather prediction, pesticide usage, weed and water management, and crop disease prevention (Jha et al. 2019, Nturambirwe & Opara 2020). These technologies are beneficial for producing high-quality raw materials for food processing and reducing the cost of harvesting and sorting. Conversely, food processing factories are usually automized through central control systems that aim at steady-state processing or follow a set procedure for batch operations that are in compliance with predetermined settings. Following the Agri-Food 4.0 paradigm, automated food processing extends the current automation development to adapt to variabilities originating from raw food ingredients and mass customization consumer demands. Specifically, automated food processing systems would collect multimodal data via (inline) sensors to characterize properties (e.g., viscosity, color, and chemical composition) of incoming raw materials and (semi)finished food products. The obtained sensor data are further analyzed by signal processing. Machine learning algorithms can be built based on these data to predict and eventually control specific functional properties of the end food products in relation to processing conditions and properties of the raw materials. Actionable tasks or a set of adapted control variables can then be generated based on the control algorithms and forwarded to the actuation system (see **Figure 1**). When actuations are required (e.g., real-time adjustment of processing parameters), machine learning models are especially useful for decision-making purposes with complex food production processes for which the underlying mechanisms are not fully established. As a final step in the automated food processing cycle, the robotic system takes actions to adjust itself to adapt or further process the food materials. After having made the adjustments, a new cycle of automated food processing begins with newly collected sensing data to continuously characterize functional properties of the food products. Such a processing cycle continues until desirable functional properties have been achieved.

Automated food processing has three key elements, i.e., data acquisition, decision-making, and automated actuations. Data acquisition is realized by implementation of sensing, which in general refers to the capability of a system to detect events, acquire data, and measure changes that

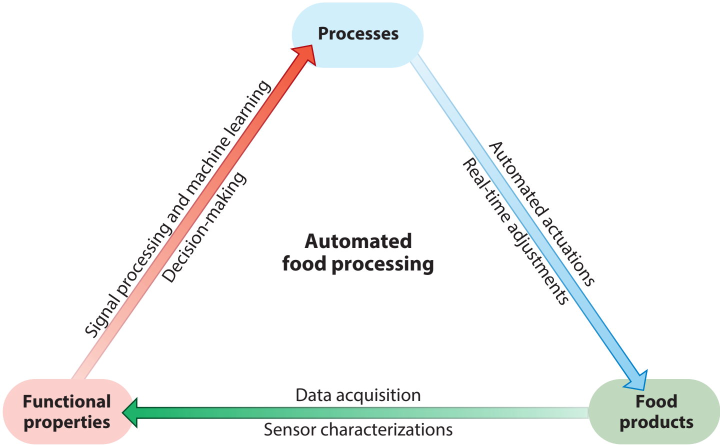

Figure 1

A conceptual illustration of automated food processing with high adaptability. Data acquisition through sensors obtain information from the foods that are produced. This information is translated into functional properties of the foods through mechanistic models, machine learning, or a combination of these. This information is compared to the desired functional properties, and automated decisions on corrective real-time adjustments can be made.

occurred in a physical environment (Miranda et al. 2019). Sensors are used for nondestructive detection of the quality and safety indicators of food (Abasi et al. 2018, Bouzembrak et al. 2019). Sensors in food manufacturing mostly measure operational conditions such as temperature, motion and displacement, velocity, and force and pressure or quality indicators (or so-called functional properties) of products such as density, pH, size, shape, and color. Some sensors surpass human perceptions to measure product physical and/or chemical properties by using hyperspectral imaging, near-infrared, ultrasound, and microwaves. Data collected by sensors can then be analyzed by various algorithms for decision-making purposes such as training a machine learning model based on classification or regression (Berrie 2013).

As the second key element, control algorithms form the intelligent connection between sensing and actuation, i.e., the decision-making "brains" of the process. Motion control of industrial robot manipulators is done via different approaches such as independent joint control and proportional–integral–derivative (PID) control. PID control is simple, and its settings are easily understood and quantified, which is preferable in industry. However, if the operation should complete complicated tasks in which the system may encounter unknown situations that are hard to predetermine, it should be able to reason the appropriate approach by itself. In this case, machine learning is a good approach to decision-making in automated food processing (see **Figure 1**). Such a machine learning approach is further elaborated in the subsequent sections.

Finally, automated food processing requires an "action." These "actions" can be as simple as opening and closing a valve to control liquid flow in a pipe, or as advanced as controlling a set of modern robotic actuators to handle discrete products. Here, we briefly discuss robotic actuators for food processing. Three types of actuators that are commonly used in industrial robots are electromagnetic, hydraulic, and pneumatic. Electric servomotors can accurately realize the desired position, velocity, and torque that change frequently and abruptly. For example, these types of motors are often used in driving the motion of a printhead or piston during extrusion-based 3D printing. Hydraulic actuators are suited for employment of large forces and high power-to-weight ratios but are less accurate than servomotors. Pneumatic actuators provide cost-effective and good performance in point-to-point motion, are not as accurate as servomotors, and are not suitable for applications requiring large forces (Siciliano & Khatib 2016). Different types of actuators can be combined in one system for specific applications. Inventories of different actuators used in industrial robots are available in the literature (Chua et al. 2003).

Sensors, machine learning algorithms, and robotic actuators together establish the pillars of automated food processing in the new era of Agri-Food 4.0. Although the three components have been separately developed into various food processing applications, automated food processing requires all three components to be integrated. The decision-making step, powered by machine learning, therefore becomes a crucial link between the measured data from food processing and the resulting effective actuations. Tailored machine learning algorithms are robust and interpret complex signals obtained from various food processing operations and optimize manufacturing actions to address variability coming from raw materials and consumer demands.

2.2. Machine Learning

Machine learning is a subfield of artificial intelligence and deals with using data to create models for decision-making purposes. The food sector has been making use of processing data for monitoring and anomaly detection purposes. For example, multivariate statistical process control (MSPC) was applied to monitor and diagnose faulty operations of a food pasteurization process (Tokatli et al. 2005). Although the MSPC approach prioritizes process consistency, it is not designed to address variabilities coming from raw materials (i.e., preprocessing variations) and consumer demands of customized food products (i.e., product requirement variations). Machine learning builds on top of MSPC to apply a set of algorithms to identify patterns in high-dimensional data. Because of the diverse range of algorithms available, machine learning is capable of linking multiple inputs and outputs together, creating robust models to capture various sources of variations found in food processing life cycles. The machine learning workflow generally includes (*a*) acquisition of training data, (*b*) selecting and/or engineering features, (*c*) model training, and (*d*) model validation and testing. Nturambirwe & Opara (2020) provide a comprehensive overview of common machine learning algorithms and corresponding learning tasks with regard to applications in food processing.

Optimizing food processes often requires creating a model of the system. A mechanistic understanding of a food processing operation can be difficult to obtain because of the intertwined influences of processing parameters on the product quality, i.e., multiple inputs and multiple outputs, and the complexity of the food materials. A typical example of such a system that has challenged food technologists for decades is extrusion. Operators struggle to identify unambiguous relations between the extrusion performance (e.g., finished product quality) and independent variables (e.g., barrel temperature). Developing mechanistic models (a white-box model) to fully capture the extrusion performance is challenging and often unrealistic because of the interconnection between many processing variables and the complex and often nonlinear response of the extruded materials. As a result, semimechanistic models are commonly applied to identify qualitative and/or semiquantitative relations between the inputs and outputs (Walstra 2002).

Data-driven machine learning (i.e., a black-box model) circumvents the requirement for mechanistic insights by capturing the correlations between the input parameters and the empirical performance. Nonlinear and multidimensional machine learning models make it possible to include the complexity of food materials and products. The models are therefore trained purely based on linking inputs and outputs from experimental data. Training such a model for a reasonably complex system requires large amounts of well-structured data. Such training data commonly exist in the form of images and spectra, leading to deep learning–based models to evaluate food qualities (e.g., detection of fruit damage and color change during storage)

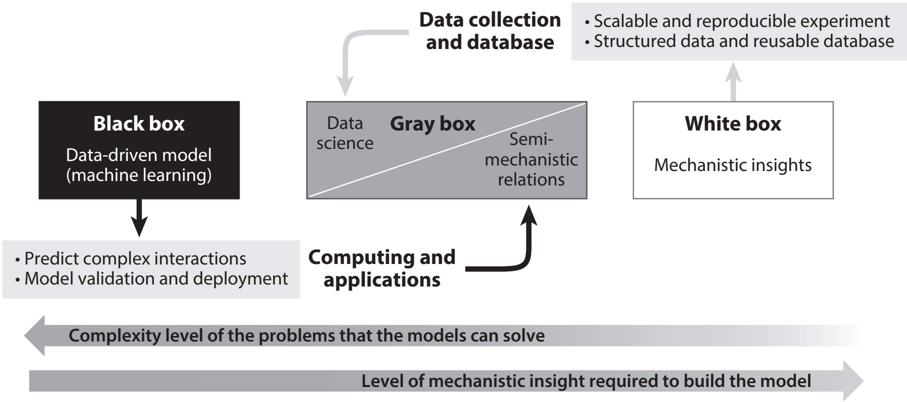

Figure 2

A conceptual illustration of different modeling approaches: black-box models (purely data-driven models), gray-box models (a hybrid modeling approach), and white-box models (mechanistic models). Inputs for gray-box models are collected and structured based on mechanistic insights into problems to be solved. Gray-box models make predictions based on data input. The models are validated with unseen data from the same database and can be deployed in the existing production system. Finally, analyzing the models may provide semi-mechanistic insights into the domain problems.

(Nayak et al. 2020). However, extending the black-box approach to model process parameters and raw ingredient compositions poses difficulties due to data scarcity and lack of relevant validations.

Because these black-box models solely capture empirical correlations in the existing data set, they are not well suited to extrapolate to unknown combinations of process parameters and/or raw ingredients. In the case that some insight into the system's behavior is known in advance, a hybrid approach (a gray box) combining the genericity of mechanistic models and the effectiveness of machine learning models can be preferable (see **Figure 2**). A gray-box modeling approach combines data-driven machine learning and first-principle models. This combination can reduce the model's complexity and consequently reduce the amount of data needed to train the model by using mechanistic insight to generate a decision from measured data. The concept of gray-box models is elaborated below, and examples are given in the form of a case study in the extrusion-based 3D printing of food.

2.3. Recent Development and Potential Applications

Machine learning may help solve problems and challenges in the food domain with high accuracy and efficiency, which are not easily solved by using traditional approaches (Sharma et al. 2020). Machine learning finds applications in the domain of food processing, ranging from formulation development and process (and unit operation) optimization to product quality assessment. For example, the techno-functional properties (e.g., viscosity) that raw food ingredients affect in end products can be predicted using machine learning models (Lie-Piang et al. 2023). Optimization of unit operations in food manufacturing such as dough mixing (Aljaafreh 2017) and beer fermentation (Bowler et al. 2021) is achieved by training models on process data acquired via sensors, which are then employed to continually adjust the process parameters. Moreover, food quality assessment tools, such as for sensorial evaluation of cheese (Rocha et al. 2020) and classifying the crispiness-related freshness of puffed snacks (Sanahuja et al. 2018), are being developed using machine learning. **Table 1** lists some representative studies related to using machine learning for food processing applications.

Table 1 Selected studies on machine learning for (automated) food processing systems

Reference	Topic
Lie-Piang et al. 2023	Machine learning models to predict techno-functional properties of less-refined food ingredients
Ma et al. 2021	Predicting extrudability of 3D food printing based on printing settings and rheological data of food inks
Bowler et al. 2020	A review on inline sensing techniques used to optimize industrial mixing processes of liquid–liquid, gas–liquid, solid–liquid, solid–gas–liquid, and solids
Sun et al. 2019	A review on intelligent drying technologies and applications
Simeone et al. 2018	Optical monitoring system based on a digital camera and ultraviolet light source to assess fouling in process tanks and predict the required cleaning time
Bowler et al. 2021	Predicting the alcohol concentration during beer fermentation with machine learning models built on ultrasonic sensor data
da Silva Cotrim et al. 2021	Nondestructive tool to classify bread-baking stages based on color changes of the crust
Du & Sun 2006	A review on applications of computer vision for food quality evaluation
Yu et al. 2018	A review on computer-based approaches to flavor and sensory analysis
Jimenez-Carvelo et al. 2019	A review on data-analyzing methods applied in food quality and authenticity
Sanahuja et al. 2018	Classification of puffed snack freshness based on crispness-related properties using data obtained from mechanical tests (i.e., force and sound)
Gonzalez Viejo et al. 2018	Assessing beer quality based on foamability and chemical composition using computer vision and near-infrared spectroscopy

The available studies mainly aimed to use machine learning models to achieve production consistency (i.e., addressing variations within the process operation itself) and/or demonstrate the process of developing machine learning models and evaluating their performances. The integration of sensing and machine learning–based decision-making into one automated food processing system is still in early development. Here, we discuss the potential of automated food processing in terms of its adaptability to (*a*) raw material variations and (*b*) varying product quality requirements. Consistency, accuracy, and reliability are key requirements for successful automated food processing.

Industrial food production starts with formulation development using raw ingredients. Raw food materials are often quite variable because of their nature as biological matter. The variability of raw food materials is expected to increase as we transition toward lower degrees of refinement to reduce the environmental footprint and address the societal pressure to produce less-processed foods. In a recent study, multiple techno-functional properties of ingredient blends from different origins were predicted using machine learning. This study demonstrated its potential to formulate food products (Lie-Piang et al. 2022, 2023). Once established, these models were used to find the parameter space available for achieving the desired products and then optimized within this space toward sustainability (e.g., global warming potential). The trained models could also aid in the identification of alternative raw materials to maintain functionality consistency for a given product application.

Variations in raw materials can complicate a production process, causing process disturbances and undesired variations in finished products. Integrating advanced sensing technologies into robotic or automated food production machinery or systems can potentially alleviate these complications. Conventional equipment in the food industry works most efficiently with large volumes of materials and products of constant quality. Raw food materials may be complex and are not always amenable to automated processing procedures (Chua et al. 2003). For example, food raw materials are not uniform in size, shape, and consistency and are often used to prepare not one but a variety of products. A sensor-integrated automated food processing system could potentially adapt to such complexity. For example, a 3D-vision-guided robotic concept could be developed for chicken fillet harvesting, which could potentially increase yield and reduce waste (Misimi et al. 2016). The developed robotic system could adapt to the birds' anatomical variations. A machine learning algorithm processes images of the fillets from an RGB-D camera, uses this information to locate the initial contact point for a grasping motion, and then employs a feed-forward algorithm to control the robot arm and generate the motions to cut off the fillet (i.e., grasp and hold, pull down, and release).

Mass customization is the progressive hypersegmentation of food products toward specific archetypes of consumers. We, as consumers, all like to prepare special and new foods to celebrate and enjoy each other's company and vary our foods to keep our palate interested, and we all have different nutritional requirements. Preferences in foods may stem from our state of nutrition (under- or overweight) or general health, our age, or our genetic or phenotypic susceptibility (Braconi et al. 2019). The current food industry excels in efficiently producing very large numbers of the same foods but not in providing every consumer with their own personal product. There is an increasing demand to address the specific needs of targeted groups of consumers. Personalized nutrition is especially useful for specific consumer archetypes such as recovering patients, pregnant women, school children, and athletes. However, our current production processes are not suitable for mass customization. Automated food processing systems and machine learning could aid in making processes more flexible toward production of smaller numbers of different products.

Automated food processing could also directly help consumers. For example, an automatic food image recognition system was developed to estimate the food intake of Parkinson's disease patients (e.g., classification and recognition of food and drink). This tool or similar ones can provide a dietary assessment to help reduce undernutrition (Mezgec & Korousic Seljak 2017) or could help with evaluation of the nutritional intake for dysphagia patients (Pfisterer et al. 2018). Sharing these data with food manufacturers could directly help product innovation. This is an example of bringing consumers closer to innovation in the food sector.

The ultimate form of automated and personalized food processing would be direct consumer–machine interaction. For example, researchers developed automated image analysis methods to validate 3D food printing accuracy measurements based on inputs from human evaluators (Ma et al. 2023b) and contextualize the computed fibrousness ratings of meat analogs with expert panel evaluations (Ma et al. 2024). Both studies show automated image analysis methods could become a standard tool integrated into formulation development, quality control, and assessment in food production.

2.4. Case Study: Machine Learning for Extrusion-Based 3D Food Printing

As an integrated process concerning both raw ingredient variations and the diverse range of consumer demand, 3D food printing positions itself as a representative case to illustrate the contribution of machine learning to empower automated food processing. Although the case is application specific, the challenges highlighted here are generic and may be translated to other types of food processing.

3D food printing, or additive food manufacturing technology, may help realize the mass customization and personalized nutrition that was discussed in the previous section because of its capability of rapid prototyping (Sun et al. 2018). However, currently available 3D food printing technology still has low adaptability to the complexity and variability of raw materials and highly customizable product designs. The variations in the functional properties of food materials containing multiple compositions (e.g., rheological properties) make both formulation design and process optimization challenging and time-consuming (Ma & Zhang 2022). The limited understanding of the relationship between the functionality of ingredients and the printing behavior of food materials (e.g., extrudability and stability) restricts the range of food product personalization. 3D food printing presents a representative case of variability challenges from raw materials and mass customizations in the field of food processing. In this case study, we discuss the use of automated food processing strategies to improve the efficiency of extrusion-based 3D food printing.

The rapid development of sensing technologies, machine learning algorithms, and robotic technologies offers new opportunities to develop the next-generation 3D food printer (Urhal et al. 2019). Specifically, the printing behavior of food materials can be monitored by vision sensors such as a digital camera or infrared camera (Ma et al. 2022). Material properties of a given food material (so-called food inks) can be reliably calibrated using computer vision techniques under relevant processing conditions (Ma et al. 2023a). Using data collected by these vision sensors, advanced signal processing based on computer vision is used to optimize processing parameters in 3D printing, e.g., printing temperature, printing speed, and moving profiles of the printhead. Some vision sensor applications can also evaluate the success and failure of the 3D printing job to quantitatively assess the degree of printing accuracy and defect rate as compared to the original digital design (Roland Outrequin et al. 2024).

The rapid and automated quality assessment based on machine vision sensors can also provide valuable labels for training machine learning models. When the monitoring and evaluation sensors are deployed to 3D food printing operations, acquired data are collected into a food printing database for machine learning applications. For example, machine learning models were built to link material rheological properties of the printed material to printing parameters based on the XGBoost algorithm (Roland Outrequin et al. 2024). Although instrumental rheological measurements can serve as valid model inputs to characterize food printing material variabilities, Ma et al. (2021) applied the Hagen–Poiseuille model for flow (i.e., mechanistic insights) to produce 3D-printer-generated variables for a gray-box prediction model that predicted the extrudability of food materials based on printing parameters and material properties. By using 3D-printer-generated variables, the gray-box model simplifies the rheological measurements for high-throughput data collection.

The empirically collected data were then used for predictive modeling, which further advances the experimental measurements into data-driven models. A combination of sensor development and predictive modeling demonstrates the concept of adaptive additive manufacturing as a showcase of an automated food processing system (see **Figure 3**). Such a 3D food printer could also be used to develop functional food products for the general public or consumers with special needs such as astronauts, school children, elderly people, and dysphagia patients.

3. CHALLENGES AND RELEVANT RESEARCH QUESTIONS

Some challenges for the future development of automated processing systems for smarter food manufacturing are foreseeable. In an industrial setting, the adaptation of robotic systems is mainly based on raw materials and semifinished product variations. Real-time parameter adjustment requires high operation speed and a very short latency time between sensing and actuation. For example, image acquisition and analysis via vision cameras could be computationally intensive, but optimized machine learning algorithms may meet the requirement for calculation speed to overcome this challenge, especially when carried out with dedicated neural processing units. In the meantime, process monitoring data may exist in different forms as images, spectra, and other multidimensional sensing signals. Developing suitable multimodal data structures therefore becomes an emerging area of research. Pre-trained foundation models in deep learning may be able to address this challenge, as these large-scale models are capable of encoding various data sources such

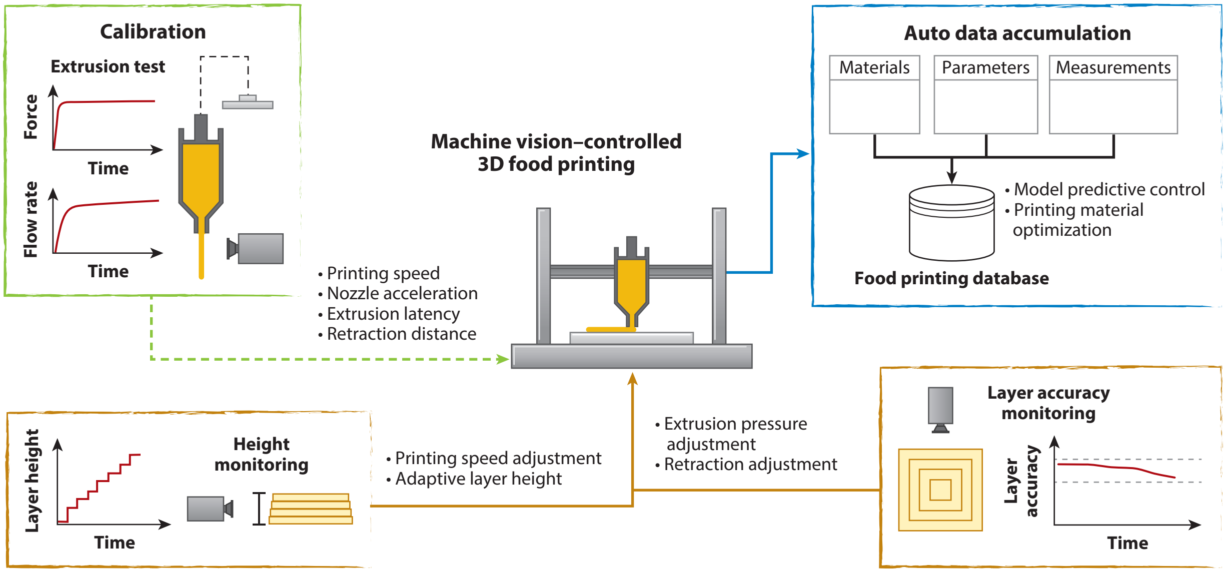

Figure 3

A conceptual design of an extrusion-based 3D food printing system integrated with vision controllers and a responsive database. Figure adapted from Ma (2024).

as images, text, and numerical inputs. The encoded data can then be further trained into specialized machine learning models that can predict parameters of interests related to food processing tasks.

In general, the cost of implementation and maintenance of such systems in existing manufacturing cycles is of great concern to food companies, as foods are low-margin products that only generate substantial profits at large quantities. Tasks performed by any automated food processing system should bring commercial advantages (e.g., increased operator safety or product quality) and should be technically feasible at low cost. Designing modular and retrofitted automated food processing units may be desirable to popularize our proposed approach. In the meantime, proper investment into digitization and automation grants opportunities to food companies to transform their current ways of working.

In a consumer or retail setting, automated systems could collect direct feedback from consumers on the changing needs and preferences. In the setting of a kitchen, restaurant, supermarket, or warehouse, automated food process systems could offer direct interaction between the machine and the consumer. These systems should operate safely under conditions that are benign to humans and would require human intervention, such as selection from a menu or changing cartridges for a 3D food printer, but would also allow feedback that could be directly translated into the adaptation of the formulation or product design, thus creating a consumer-driven product automation feedback loop.

Future development of automated process systems for sustainable food production requires a multidisciplinary approach that combines knowledge in the fields of process engineering, mechanical engineering, systems engineering, and social science (e.g., human–robot interaction, consumer behavior). Implementing closed-loop control strategies will help deploy automated sensor data analysis methods in real food production. When designing control algorithms based on inline sensor data, inputs from users of the machinery could also be taken into account to improve the relevance of the control action (e.g., changing 3D printing settings to achieve print quality that is approved by the consumers). In addition, to further implement a functionality-driven approach for food formulation, developing a robotic platform equipped with analytical instruments (e.g., inline sensors) to automatically measure the properties of food materials is necessary to avoid a labor-intensive experiment. For this, standardized analytical methods (e.g., gelling properties, water-holding capacity, emulsifying properties) for food material properties need to be developed to ensure the quality of the obtained data and improve the applicability of the results in different lab settings.

4. CONCLUSIONS

In this review, we discussed machine learning applications that enable automated food processing with high adaptability against raw material variations and mass customization. Such adaptivity will eventually be beneficial in designing healthy and tasty foods, optimizing process conditions for sustainable food production, realizing mass customization of food for personalized nutrition, and facilitating human–machine interaction. We also expect that further development of such systems will accelerate the integration of a more sustainable food supply chain based on the joint force from academia and industry.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

The authors would like to acknowledge the National Sectorplan Techniek for funding the research on additive food assembly at the Laboratory of Food Process Engineering, Wageningen University & Research.

LITERATURE CITED

Abasi S, Minaei S, Jamshidi B, Fathi D. 2018. Dedicated non-destructive devices for food quality measurement: a review. *Trends Food Sci. Technol.* 78:197–205

Aljaafreh A. 2017. Agitation and mixing processes automation using current sensing and reinforcement learning. *J. Food Eng.* 203:53–57

Berrie PG. 2013. Sensors for automated food process control: an introduction. In *Robotics and Automation in the Food Industry*, ed. DG Caldwell, pp. 36–74. London: Woodhead Publ.

Bouzembrak Y, Klüche M, Gavai A, Marvin HJP. 2019. Internet of Things in food safety: literature review and a bibliometric analysis. *Trends Food Sci. Technol.* 94:54–64

Bowler A, Escrig J, Pound M, Watson N. 2021. Predicting alcohol concentration during beer fermentation using ultrasonic measurements and machine learning. *Fermentation* 7(1):34

Bowler AL, Bakalis S, Watson NJ. 2020. A review of in-line and on-line measurement techniques to monitor industrial mixing processes. *Chem. Eng. Res. Des.* 153:463–95

Braconi D, Cicaloni V, Spiga O, Santucci A. 2019. An introduction to personalized nutrition. In *Trends in Personalized Nutrition*, ed. CM Galanakis, pp. 3–32. Cambridge, MA: Academic Press

Chua PY, Ilschner T, Caldwell DG. 2003. Robotic manipulation of food products—a review. *Ind. Robot.* 30:345–54

da Silva Cotrim W, Felix LB, Minim VPR, Campos RC, Minim LA. 2021. Development of a hybrid system based on convolutional neural networks and support vector machines for recognition and tracking color changes in food during thermal processing. *Chem. Eng. Sci.* 240:116679

Du C-J, Sun D-W. 2006. Learning techniques used in computer vision for food quality evaluation: a review. *J. Food Eng.* 72:39–55

Gonzalez Viejo C, Fuentes S, Torrico D, Howell K, Dunshea FR. 2018. Assessment of beer quality based on foamability and chemical composition using computer vision algorithms, near infrared spectroscopy and machine learning algorithms. *J. Sci. Food Agric.* 98:618–27

Gray JO, Davis ST. 2013. Robotics in the food industry: an introduction. In *Robotics and Automation in the Food Industry*, ed. DG Caldwell, pp. 21–35. London: Woodhead Publ.

Jha K, Doshi A, Patel P, Shah M. 2019. A comprehensive review on automation in agriculture using artificial intelligence. *Artif. Intell. Agric.* 2:1–12

Jimenez-Carvelo AM, Gonzalez-Casado A, Bagur-Gonzalez MG, Cuadros-Rodriguez L. 2019. Alternative data mining/machine learning methods for the analytical evaluation of food quality and authenticity—a review. *Food Res. Int.* 122:25–39

Khan MIH, Sablani SS, Nayak R, Gu Y. 2022. Machine learning-based modeling in food processing applications: state of the art. *Compr. Rev. Food Sci. Food Saf.* 21:1409–38

Khan ZH, Khalid A, Iqbal J. 2018. Towards realizing robotic potential in future intelligent food manufacturing systems. *Innov. Food Sci. Emerg.* 48:11–24

Kjetil Jørgensen TN. 2004. A design and analysis strategy for situations with uncontrolled raw material variation. *J. Chemom.* 18:45–52

Lie-Piang A, Hageman J, Vreenegoor I, van der Kolk K, de Leeuw S, et al. 2023. Quantifying techno-functional properties of ingredients from multiple crops using machine learning. *Curr. Res. Food Sci.* 7:100601

Lie-Piang A, Moller AC, Kollmann N, Garre A, Boom R, van der Padt A. 2022. Functionality-driven food product formulation—an illustration on selecting sustainable ingredients building viscosity. *Food Res. Int.* 152:110889

Ma Y. 2024. *3D food printing: monitoring, quality assessment and adaptation with machine vision*. PhD Diss., Wageningen Univ. Res., Wageningen, Neth.

Ma Y, Potappel J, Chauhan A, Schutyser MAI, Boom RM, Zhang L. 2023a. Improving 3D food printing performance using computer vision and feedforward nozzle motion control. *J. Food Eng.* 339:111277

Ma Y, Potappel J, Schutyser MAI, Boom RM, Zhang L. 2023b. Quantitative analysis of 3D food printing layer extrusion accuracy: contextualizing automated image analysis with human evaluations: quantifying 3D food printing accuracy. *Curr. Res. Food Sci.* 6:100511

Ma Y, Schlangen M, Potappel J, Zhang L, van der Goot AJ. 2024. Quantitative characterizations of visual fibrousness in meat analogues using automated image analysis. *J Texture Stud.* 55(1):e12806

Ma Y, Schutyser MAI, Boom RM, Zhang L. 2021. Predicting the extrudability of complex food materials during 3D printing based on image analysis and gray-box data-driven modelling. *Innov. Food Sci. Emerg.* 73:102764

Ma Y, Schutyser MAI, Boom RM, Zhang L. 2022. Thermographic and rheological characterization of viscoelastic materials for hot-extrusion 3D food printing. *Innov. Food Sci. Emerg.* 81:103135

Ma Y, Zhang L. 2022. Formulated food inks for extrusion-based 3D printing of personalized foods: a mini review. *Curr. Opin. Food Sci.* 44:100803

Mezgec S, Korousic Seljak B. 2017. NutriNet: a deep learning food and drink image recognition system for dietary assessment. *Nutrients* 9(7):657

Miranda J, Ponce P, Molina A, Wright P. 2019. Sensing, smart and sustainable technologies for Agri-Food 4.0. *Comput. Ind.*108:21–36

Misimi E, Øye ER, Eilertsen A, Mathiassen JR, Åsebø OB, et al. 2016. GRIBBOT—robotic 3D vision-guided harvesting of chicken fillets. *Comput. Electron. Agric.* 121:84–100

Nayak J, Vakula K, Dinesh P, Naik B, Pelusi D. 2020. Intelligent food processing: journey from artificial neural network to deep learning. *Comput. Sci. Rev.* 38:100297

Nturambirwe JFI, Opara UL. 2020. Machine learning applications to non-destructive defect detection in horticultural products. *Biosyst. Eng.*189:60–83

Pfisterer KJ, Amelard R, Chung AG, Wong A. 2018. A new take on measuring relative nutritional density: the feasibility of using a deep neural network to assess commercially-prepared puréed food concentrations. *J. Food Eng.* 223:220–35

Rocha RS, Calvalcanti RN, Silva R, Guimarães JT, Balthazar CF, et al. 2020. Consumer acceptance and sensory drivers of liking of Minas Frescal Minas cheese manufactured using milk subjected to ohmic heating: performance of machine learning methods. *LWT* 126:109342

Roland Outrequin TC, Gamonpilas C, Sreearunothai P, Deepaisarn S, Siriwatwechakul W. 2024. Machine learning assisted evaluation of the filament spreading during extrusion-based 3D food printing: impact of the rheological and printing parameters. *J. Food Eng.* 381:112166

Sanahuja S, Fédou M, Briesen H. 2018. Classification of puffed snacks freshness based on crispiness-related mechanical and acoustical properties. *J. Food Eng.* 226:53–64

Sharma R, Kamble SS, Gunasekaran A, Kumar V, Kumar A. 2020. A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. *Comput. Oper. Res.* 119:104926

Siciliano B, Khatib O, eds. 2016. *Springer Handbook of Robotics.* Berlin: Springer

Simeone A, Deng B, Watson N, Woolley E. 2018. Enhanced clean-in-place monitoring using ultraviolet induced fluorescence and neural networks. *Sensors* 18(11):3742

Sun J, Zhou W, Yan L, Huang D, Lin L. 2018. Extrusion-based food printing for digitalized food design and nutrition control. *J. Food Eng.* 220:1–11

Sun Q, Zhang M, Mujumdar AS. 2019. Recent developments of artificial intelligence in drying of fresh food: a review. *Crit. Rev. Food Sci. Nutr.* 59:2258–75

Tokatli F, Cinar A, Schlesser JE. 2005. HACCP with multivariate process monitoring and fault diagnosis techniques: application to a food pasteurization process. *Food Control* 16:411–22

Urhal P, Weightman A, Diver C, Bartolo P. 2019. Robot assisted additive manufacturing: a review. *Robot.Comput.-Integr. Manuf.* 59:335–45

Walstra P. 2002. *Physical Chemistry of Foods*. Boca Raton, FL: CRC Press

Yu P, Low MY, Zhou W. 2018. Design of experiments and regression modelling in food flavour and sensory analysis: a review. *Trends Food Sci. Technol.* 71:202–15

Zhu L, Spachos P, Pensini E, Plataniotis KN. 2021. Deep learning and machine vision for food processing: a survey. *Curr. Res. Food Sci.* 4:233–49