International Journal of Applied Smart Interdisciplinary Technologies (IJASIT)

Home Page: https://ijasit.org **ISSN: 3139-759X**

https://doi.org/10.68104/ijasit.v1.i3.30

Advances in Agricultural and Food Processing Sectors using Artificial Intelligence

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Article History:
Received Date: 08 August 2026
Revised Date: 18 August 2026
Accepted Date: 26 August 2026
Published Date: 11 September 2026

Keywords:

AI; Machine learning; Bakery industry; Dairy Processing; Fruit processing; Sensors

ABSTRACT

The three most attention attractions from the food industry are nutritional value, food quality, and processing methods. Subsequently, the food industry is experiencing growing pressure from consumers who are demanding foods that are of high quality, excellent taste, and long shelf life. Advanced applications in the food industry are today carried out using deep learning, AI, and ML algorithms. Ideally, as technology in AI and ML continues to improve, dealing with drifting issues that surround food processing has become easier. Circular economy-based models help maintain resources within the system by utilizing one of the 10 R processes: A few of these include: Recycle, Rethink, Remanufacture, Repurpose, Recover, Refurbish, Refuse, Reuse, Repair, and Reduce. A more efficient supply chain management system is needed to increase food packaging, shelf life and food safety. This article highlights some of the ways AI and ML are being used in food processing and preservation, including in logistics management, the baking industry, food, dairy and fruit processing, meat production, and the preservation of food processing tools.

1. Introduction

It is interesting to note that the food industry is undergoing significant changes with the integration of artificial intelligence (AI) and machine learning (ML). These technologies are being applied through robots and automated systems to enhance the quality of processed foods. AI is relatively a new focus of research and innovation across various domains, including food and nutrition, quality control, science, engineering, medicine, marketing and supply chain management. Smart innovation and an increased emphasis on research in artificial intelligence have become essential due to the major developments spurred by the Fourth Industrial Revolution, particularly through advancements in AI [1]. Estimates suggest that by 2050, the global population will range between 9 and 10 billion, requiring a 60% to 110% increase in food production to meet demand [2–4].

The world must pursue sustainable agriculture and improve methods of delivering food to overcome food security challenges and combat hunger. In this context, production challenges and food safety remain significant concerns. Food safety crises, such as bovine spongiform encephalopathy and the dioxin contamination of poultry, were catastrophic events that highlighted the importance of adequate and efficient traceability systems in the supply chain [5,6]. The latest smart traceability systems can promote transparency, optimize recall operation, and build consumer trust. The role of the food industry extends beyond processing and packaging to enhancing the quality of food available in the market. AI in food processing includes the use of big data and analytics to manage processing equipment management, leveraging recipe information, and employing sensors and machine learning for real-time quality control [7–9]; (Fig. 1). For example, in bakery and dairy products, AI is used to improve and maintain production quality, while in fruit and vegetable processing, AI is applied sorting, grading, and ensuring quality standards are met [10–14]. Similarly, precision farming systems, which include smart agricultural tools, are supported by satellites, IoT, and machine learning models to reduce input usage, minimize environmental impact, and increases yield [15,16]. The impact of AI in these systems enhances input efficiency, reduces environmental strain, and improves productivity [17–19]. These technologies play a crucial role in addressing the challenges of sustainable food production while the circular economy principle of minimizing waste and promoting efficient resource use [20–25]. In the future, AI and related technologies are expected to be key drivers of sustainable development and essential in the fight against hunger as global population grows [1,26].

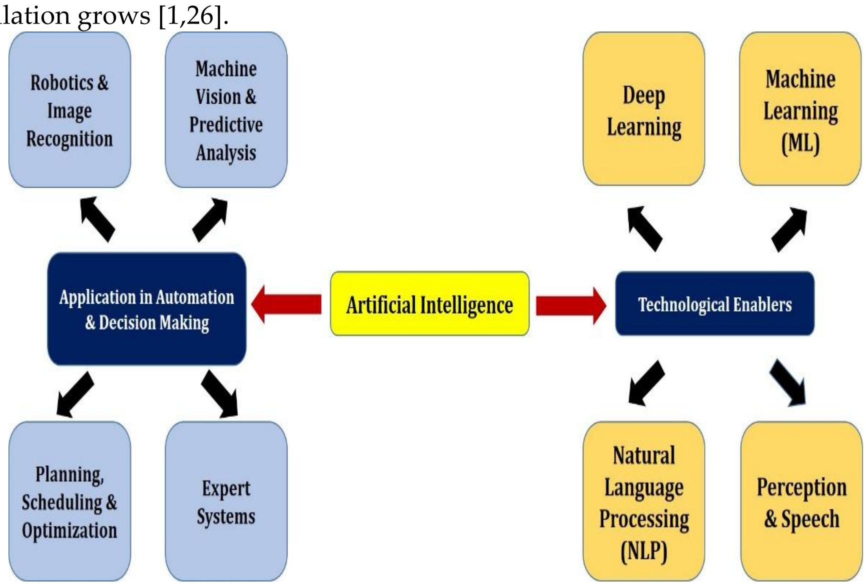

Fig. 1. Artificial Intelligence Sectors

The global food industry faces an inevitable surge in demand due to the increase in the world population [27]. Industry 4.0, recognized as the fourth industrial revolution in manufacturing, is fostered and powered by the latest and fastest technologies, including smart drones, 3D printing, sensors, and smart robots in the food industry [28–32]. This aligns information and digital manufacturing technologies, offering new opportunities and approaches to proactively adapt sustainable and smart manufacturing [33,34]. AI is gaining importance in food processing to support the supply chain, enhance customer relations, optimize resource use, and increases productivity [5,35]. Some applications focus on establishing concrete methodologies to monitor product quality, standardize it, and offer new approaches to consumers at a lower cost [36,37]. Innovative AI based solutions, often in combination with deep learning (DL) concepts, have been helpful for implementing computerized visual inspections, fault recognition and predictive maintenace thus providing improved reliability and effectiveness of production systems [38].

Production methologies, such as material handling systems and production scheduling, are also experiencing major changes through AI-based techniques [8,39,40]. Real time data analysis, supported by AI, cyber-physical systems, and Internet of Things (IoT) enables industries make the right decisions. These systems operate in a smart environment where real-time interaction is achievable, large amounts of data can be processed, and seamless integration between sensors, operators, and machines is facilitated [41]. Industry 4.0 represents the integration of key manufacturing functions into a cohesive network, resulting in better resource utilization, reduced waste, lower energy consumption, and improved adaptability and output [42,43].

The success of Artificial Intelligence (AI) integration within the Nordic food processing sector is characterized by its precise application toward sustainability and operational efficiency, driven by the region's high technical standards. Key successes leverage Machine Learning (ML) and computer vision systems to automate and optimize resource-intensive stages. For instance, ML algorithms are deployed for predictive maintenance of complex processing lines, effectively minimizing unexpected downtime and maximizing asset utilization, while advanced computer vision systems perform real-time quality grading and defect detection in products like fish and dairy, leading to reduced material loss and enhanced compliance. While the region's overall AI adoption pace may be measured, its achievements are rooted in a strategic, data-centric approach focused on creating resilient, traceable, and highly efficient food systems that adhere to strict Nordic and EU environmental protocols.

Converting operations, of course, solves most of the obstacles of the food industry. The future of the food manufacturing lies in the application of DL, ML, and AI systems for automation and better data control [7]. AI ensure compliance with objectives, industry standards, and food safety and quality assurance, as well as the effectiveness and solidity of processes, thus reducing their costs [44–46]. Self-driving technologies and AI based systems offers several advantages to the agri-food supply chain, including lower dependency on human labor, faster problem-solving, improved staff training, fewer human induced errors, and improved decision making. These technologies provide efficient, optimal real-time approaches to solving crucial operational issues, thereby enhancing the sustainability of the sector [47–49]. Therefore, the incorporation of the two technologies-AI and ML- into the food and agri-food sectors should be considered a paradigm shift. Addressing major concerns related to food safety, quality, and production efficiency, while introducing the concept of a smarter food chain.

2. AI in the Food Industry

AI and ML, which have emerged in recent years, are increasingly recognized for their broad range of applications in solving various issues. These technologies have been applied in areas such as modeling, classification, and data analysis. It is particularly suitable for handling complex data, enhancing relationships, and analyzing information from processes like gas chromatography, high-performance liquid chromatography, mass spectrometry, pyrolysis, etc. [50]. Some AI systems are designed for RNA and DNA sequence identification, protein structure analysis, biomass characterization, determining shelf life of food products, predicting the growth of microbes, and identifying microbes, among other applications [51]. Additionally, the integration of fuzzy logic and genetic algorithms, is making its way into food processing and engineering, helping to improve system performance, particularly neural networks [52–54].

AI has shown significant potential in enhancing food quality and has made substantial contribution to advancements in food science and processing. Cleanliness is a critical priority in the food sector, maintained through Clean-In-Place (CIP) Clean-Out-of-Place (COP) systems. AI plays a key role in optimizing these systems, with a self-optimizing version known as SOCIP (Self-Optimizing Clean-in-Place) now being implemented to ensure efficient cleaning [55,56]. Due to the ever- increasing population, shrinking arable land, climate change, and pollution, food production often fails to meet the demands of the global population [57,58]. These challenges have significant impact on human health, the environment, and nutritional status with over six billion people still experiencing malnutrition. To address these challenges and ensure the long-term effectiveness of goals and objectives, various strategies/approaches are necessary. These include reducing vulnerabilities that lead to food insecurity, increasing and diversifying dietary nutrient intake, and adopting sustainable practices for the limited natural resources in Agriculture (Fig. 2).

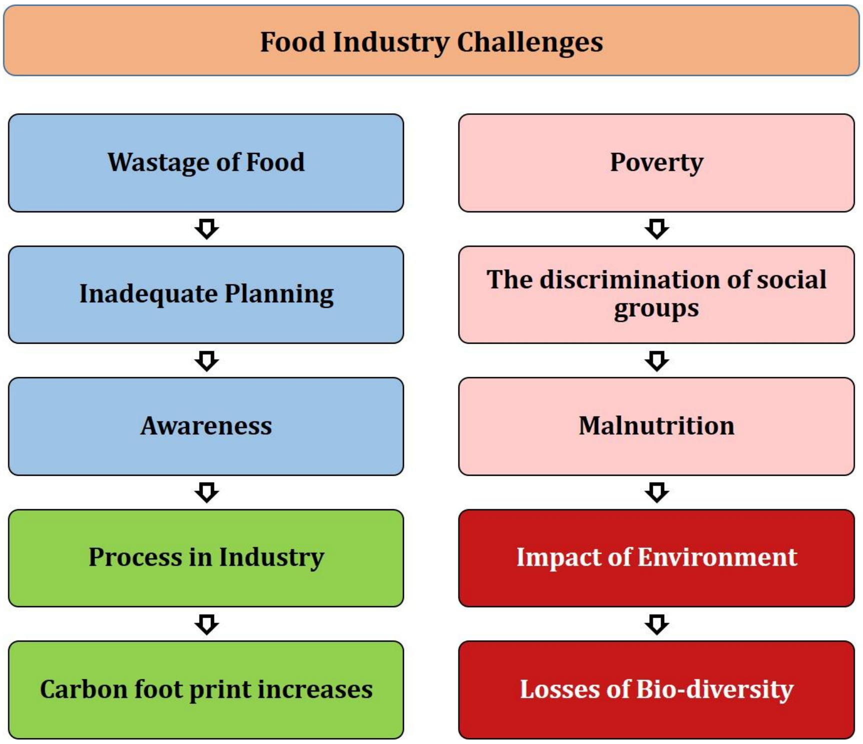

Fig. 2. Food Industry Challenges

2.1 Dairy Processing

Milk products are transported in milk trucks from various production centers to processing plants. Upon arrival at the plant, the milk undergoes pasteurization, a crucial step in preventing bacterial growth and extending shelf life [59]. Pasteurization also helps protect the milk from harmful microorganisms. The optimal pH for milk is 6.7; when the pH drops below this level, milk spoils more quickly. Preservation techniques, such as refrigeration are commonly used to maintain the freshness of milk. Refrigeration units are typically located at milk collection and help direct milk-laded trucks to collection centers, reducing the risk of spoilage. To further address this challenge, the integration of wireless sensor networks (WSNs) with artificial intelligence (AI) can enhance monitoring and quality management of milk throughout the supply chain [60,61] Table 1. AI is also being employed in the milking process itself [62–64]. Traditionally, milking cows required significant time and effort, but the process can now be expedited using Automated Milking Systems (AMS), also known as milking robots [65,66] Table 2.

Table 1 Digital driven technologies in food processing applications

Intelligent systems	Food applications	Technology used	References
AI-Guided Enzyme Engineering for Food Processing	Pumpkin seed proteins were broken down into smaller pieces using AI and enzymes to produce a flavor similar to chicken.	The enzymes contributed to the release of umami-boosting substances (GMP and IMP) and essential amino acids (like glutamate), which give food a savory flavor.	[67]
AI-Powered Microbial Fermentation Optimization	Milk permeate was integrated to improve its functionality and optimized sesame milk extraction using artificial neural networks (ANN). While permeate (5:1	Permeate integration and AI-driven optimization are two promising strategies for creating premium plant-based milk substitutes.	[68]

	ratio) increased nutrition, taste, and probiotic potential, ANN increased total solids yield (95.18%).		
Deep Learning for Food Safety & Contaminant Detection	Automating the detection of fecal contamination on meat carcasses using fluorescence imaging and deep learning	U-Net accurately segmented fecal residues (IoU 89.34%), while EfficientNet-B0 detected contaminated areas with 97.32% accuracy. These results lend support to the use of AI-driven detection for better HACCP compliance and meat processing.	[69]
AI-Based Protein Structuring in Novel Food Development	Artificial intelligence (AI)-powered tools support experimental techniques such as mass spectrometry, NMR, and X-ray crystallography while enhancing predictions for oligomers, membrane proteins, and intrinsically disordered proteins (IDPs).	Deep learning models powered by artificial intelligence (AI), particularly AlphaFold2 (AF2) and RoseTTaFold (RF), for predicting protein structures. To forecast 3D protein conformations, these models make use of neural networks, multiple sequence alignments (MSAs), and attention-based architectures.	[70]
Predictive Maintenance in Food Processing Equipment	Real-time machine data is gathered by sensors and Internet of Things devices, which then send it to cloud-based systems for analysis using machine learning algorithms to forecast malfunctions. To help prevent contamination and improve equipment efficiency, a variety of sensors track temperature, humidity, vibration, oil spray, and power consumption.	Combining IoT, AI-driven predictive maintenance, and smart technologies in food processing machinery	[71]
AI-Optimized Spray Drying & Encapsulation Technologies	Multi-layer perceptron networks (MLPN) are used to optimize the spray drying processes of fruits and vegetables. During convection and spray drying, AI improves prediction, classification, and quality control, increasing	Color, texture, moisture content, air temperature, and drying time are important drying parameters that affect yield and the quality of the finished product. A viable substitute for process optimization and longer	[72]

	productivity, lowering costs, and producing higher-quality products.	shelf life is AI-driven drying technology.	
AI-Driven 3D Food Printing & Material Extrusion Optimization	AI-enhanced 3D food printing technique that combines simultaneous infrared heating and extrusion-based printing to increase food safety and quality. This method solves problems like shape retention, ink modification, and microbial contamination by enabling in-line, quick cooking of starch-based foods using noncontact graphene heaters.	AI improves the creation of food patterns, and microstructure analysis and heat transfer simulations maximize process effectiveness. By increasing the possibilities for creating personalized, useful food, this integrative method advances the use of heating-based 3D printing in the food sector.	[73]
Machine Learning for Pasteurization Control	Fuzzy logic algorithm (a nonlinear solver engine, polynomial mixture modeling, and a modified Takagi-Sugeno approach) for mixed fruit beverage formulation optimization.	Pasteurization conditions were established using kinetic modeling and thermal pulse inactivation, which preserved essential nutrients while guaranteeing microbial and enzyme stability.	[74]
AI-Driven Smart Packaging & Shelf-Life Prediction	AI-driven predictive models (machine learning, CNN, hybrid AI) combined with IoT-enabled sensors, spectroscopy, and real-time monitoring to estimate food spoilage.	Applications include smart packaging, supply chains, and retail inventory management, aiming to improve food security and waste reduction.	[75]

In addition to milking, robotic technologies are also utilized in various stages of dairy product processing. For instance, in cheddar cheese production, robots are employed for bundling, cutting and shaping into sizes that meet consumer preferences [51]. Equipped with specialized grippers, these robots can pick up blocks of cheese and transfer them onto conveyors, where they are directed to block-forming lines [76,77]. Quality assessment of dairy products involves both internal and external attributes. Internal factors include texture, nutritional value, pesticide residues, and contamination, while external factors encompass shape, size, and pigmentation, color changes during storage, packaging conditions, and shelf life prediction [78]. To evaluate food quality, both traditional food inspectors and advanced measurement tools are used. For external quality assessment, various types of Computer Vision Systems (CVSs) are employed, including traditional CVSs, hyperspectral CVSs, and multispectral CVSs, which provide detailed insights into product quality [79].

Table 2 ANN role in Dairy Industry [51]

Technique name	**Model Name**	**Input specifications (Input)**	**Specifications (Output)**	**Uses**	**Point of summary**
ANN	MLR and Radial basiss	Spore count (SC), Soluble Nitrogen (SN),	Sensory (Shelf life)	Coefficient of determination (R2), Mean square	High correlation with MLR for predicting shelf

		Yeast count (YC), pH, Mould count (MC), (SPC)		error (MSE), Root Mean Square Error (RMSE), Nash – Sutcliffe coefficient (E^2)	life of processed cheese at 30°C. MLR is more effective than Radial Basis for predicting instant coffee shelf life.
TDNN	Multi-layered Perceptron Network	SC, SN, YC, MC, pH, SPC.	Sensory (Shelf life)	RMSE, R^2, E^2, MSE	Correctly predicted the shelf life of processed cheese for 30 days using both single and a multilayer perceptron network.
ANN	Linear Model and Radial Basis	Texture, FFA, Flavor, Moisture, Aroma	Sensory (Shelf life)	R^2, E^2, MSE, RMSE	Radial basis models are more effective than linear models in predicting the shelf life of processed cheese
ANN	General Regression Model & Linear layer	pH, SC, MC, YC, SN , SPC	Sensory (Shelf life)	(E^2), (R^2), (RMSE), (MSE)	The generalized regression model is the most effective compared to other models for predicting the shelf life.

2.2 Product Sorting and Packaging

According to the research, one of the most time-consuming and labor-intensive task in manufacturing units is the arranging and packing of food products. Implementing AI based system for sorting and packing can help to reduce errors in this process and improve production efficiency [10]. However, developing AI for sorting and packaging of fruits and vegetables presents challenges due to their irregular shapes, sizes and colors [80]. To address this, a large amount of data must be collected to ensure AI-based system performs optimally and without time wastage. Many research groups have attempted to address this problem with the help of various technologies. For instance, use of ToMRS system has proven effective, achieving an accuracy level of 90% in sorting tasks and thereby increasing production rates [81]. Currently, most sorting and packaging processes are performed by the automated systems. These systems offer several benefits, such as high production rates, improved yield quality, and reduced labor cost. The intelligent decision making tools and technologies used by AI systems include high resolution cameras, lasers, X rays and infrared spectroscopy [7]. These technologies assess the quality and suitability of fruits and vegetables for sorting and packaging. Some of the equipment commonly used in the industry includes Optical Belt Sorting Machines; Blizzard Sorting Machines; Field Potato Sorting Machines (FPS), which minimize sorting time for fruits, vegetables and individual meat portions [82] Fig. 3.

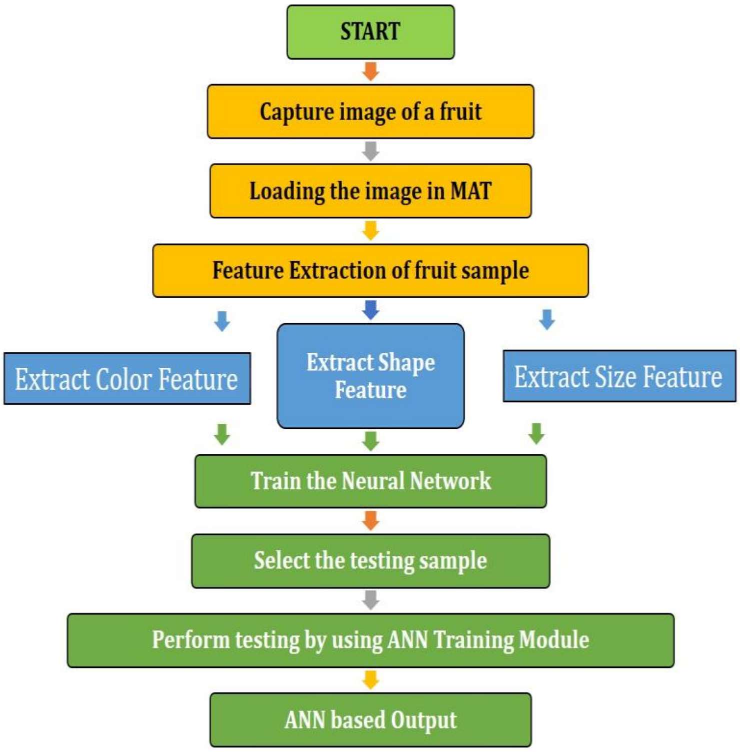

Fig. 3. Image Processing proposed system for quality detection of fruits by using ANN

Apart from the sorting and packaging, AI and robotics are adopted for most of the food processing and production functions because they do not compromise on hygiene [83]. In this regard, robots are less likely to transport hazardous bacteria or diseases in comparison to humans working in the food industry. A technavio's report reveals that, an average, three out of every ten food industries are likely to use robots in the near future, as government policies encourage this shift [84]. Additionally, new approaches in AI technologies are being developed in food safety and reduce food-borne illnesses. Two next-geberation AI technologies are being developed in the food safety domain:Next Generation Sequencing (NGS) and Electrical Nose technologies. Because, NGS enables the simultaneous detection of multiple pathogens in food sample, lab testing for food contamination is now faster and far more effective than conventional testing methods in food testing laboratories [85–87]. Likewise, electrical nose technology acts as an analytical tool that mimics olfaction, allowing it to identify chemical odors during food processing and in laboratories (Bonah et al., 2020). Each of these technologies plays a key role in ensuring that even a single impurity is detected and then removed before being incorporated into the food processing system.

2.3 Decision-Making System for Customers

Technology, particularly AI, is now playing a crucial role not only in creating new flavors in the food industry but also in advising customers on which foods are best suited to their tastes and preferences. AI is revolutionizing customer experience by providing specific food products that suit a customer's preferences, as well as introducing new flavors [88]. The use of AI in consumer decision making is also on the rise, helping brands to create a portfolio that meets individual preferences which is vital for innovation. One good example is the Bear-Naked-Custom that Kellogg launched in 2018 where consumers were allowed to select from more than 50 ingredients [89]. Customer data, including preferences and tastes are tracked within the system to provide relevant recommendations [90].The insights gained from this type of data collection are particularly important for food companies as they helps define the direction of creating new products and unique concepts that meet specific consumer needs [91]. In addition, through the information collected from consumers, AI-driven platforms can make decisions that are constantly changing, providing companies real-time information so they can update their product offerings to match new consumer preferences and introduce relevant new products seamlessly [92]. As AI technologies evolve, these systems will become even more intelligent, offering a better understanding of consumer behavior and enabling more precise food product customization [93].

Therefore, AI is not only transforming how flavors are created but also providing brands with the tools to better understand their customer base and remain relevant in a world where consumers are increasingly attuned to personalized experiences.

2.4 Baking Industry

The use of technology has been adopted in most companies and organizations, and the baking business is no exception [94]. Technological advancement is brewing in the baking industry as the consumers demand specialty products in entrepreneurship. While, artisanal products may seem to go against the trends of automation, however, automation can prove quite advantageous to bakeries, giving them a competitive edge in the marketplace. It has also been evidenced that various sorts of processes in various large scale production lines can greatly be benefitted with the help of AI driven systems. Another clear benefit of AI in cake making business is the production capability where the business can produce more cakes [95]. The use of artificial intelligent machines can produce higher volumes of production, more efficiently than human operators. Self-timing machines, production rotators, and programmable systems help ensure consistent product quality [96].

In bread production there are several processes involved, some of which require the addition of living microorganisms, such as yeast, into the dough. Failing in any of the stages can have a significant effect on the final bread produced [97]. Computerization and automated control systems (ACS) in bakeries help achieve greater profitability and improved product quality [98]. By adding sensors, bakeries can track and manage important characteristics such as rheological properties of dough and/or of sourdough, lift force, active acid, temperature, humidity, and dough weight that will lead to higher consistency [99]. These intelligent systems support managerial decision-making by integrating sensor data, databases, and expert systems, with the added benefit of flexibility in operational modes. In the bakery industry, quality sensors that measure food quality convert responses to food attributes to electrical signal [100]. For instance, microstructure characteristics such as the size and shape of bread loaf porosity can be observed through camera while examining the interior of a loaf [101]. Data obtained from these devices can be analyzed in real time hence enables enhancement of monitoring of bakery products consequently enhancing their efficiency and quality as stated by [102]. Due to AI's help aids and automation these processes have become more efficient in handling the increasing demand for bakery products while maintaining the quality of the baked goods.

2.5 AI in the Beverage industry

The beverage industry include companies that manufacture non-alcoholic beverages including coca cola, juices, thumbs up, milk, Miranda, carbonated water, soft drinks, beer, wine, spirits and other alcoholic drinks [84]. In brewing, yeast is introduced to aerated word initiating of the fermentation process. The yeast feeds on sugar in the wort, on which it metabolizes to perform the process of brewing. Certain conditions, such as temperature, oxygen content and pitching rate should be kept keenly monitored throughout the fermentation process for proper production. The quality of fermentation is affected by yeast health and composition of the wort. Brewing beer can be time consuming and inefficient using traditional methods. However with the integration of AI and other technological advancement, the brewing is can be continuously observed and run making the final product much more standardized and superior in quality. Previously, changes and adjustments may be done manually, but with help of AI most of these tasks can be done much faster, minimizing the chances of human error [103]. In modern brewing, AI and sensor employed during quality control systems (CVS) which consist of cameras, light, and computers. These systems capture high-resolution digital images of the exterior of the beer to assess its clarity and color and carbonation level [84]. Additionally, these captured images can be compiled with qualitative data by AI-enabled systems to process and analyzed the results in real-time. This enables brewers to make precise and accurate decisions about production quality and its consistency through digitization [104,105]. AI has introduced changes and improvement in formulas, manufacturing methods, and product quality, as well as facilitating expansion into new markets.

2.6 Food safety

Sensors combined with AI and ML techniques such as FL or ANNs, are revolutionizing real-time food safety detections. To improve the accuracy and speed at which food safety issues are detected, various sensor technologies are being used such as electronic tongues, electronic noses, CVS and NIRS [106,107]. These technologies are often integrated to enhance the detection accuracy, which enables early detection of contamination or spoilage (Fig. 4 and Fig. 5).

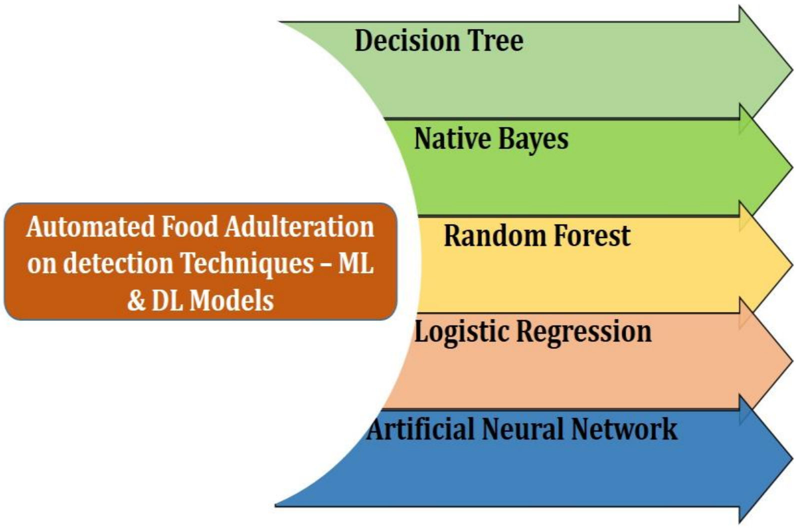

Fig. 4. Machine Learning and Deep Learning based Adulteration detection Techniques [108]

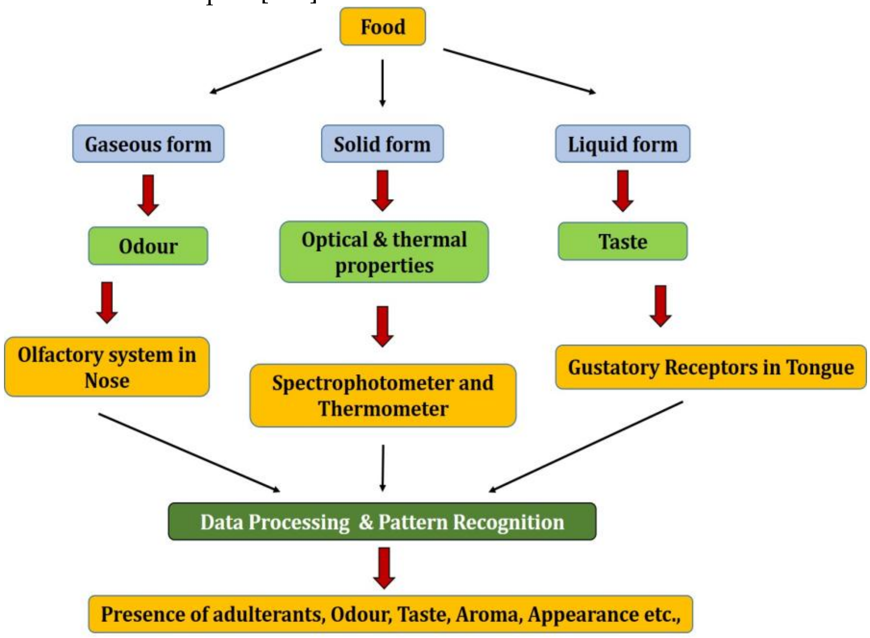

Fig. 5. An architectural perspective of E-Tongue & E-Nose [108]

Machine learning techniques apply to sensor data, enabling predictive data analysis based on the large data sets obtained [109]. These validated predictive markers help food producers to anticipate conflicts in the production process, to minimizing risks related to food safety [110,111]. An electronic nose (E-nose) is an apparatus that has resemblance to the olfactory system and comprises a number of chemical sensors used to identify both simple and composite smells. It is more accurate than other types of detectors because it is able to identify even slight variations in the quality of food by detecting volatile compounds [112]. Similarly, the electronic tongue (E-tongue) function like E-nose but it sense taste-related parameters, such as bitterness, sweetness or acidity. Both the E-nose and E-tongue are readily capable of specific elemental or molecular recognition of the hazardous organic or inorganic material, offer greater efficiency compared to conventional testing methods. Another AI technology steadily gaining traction in food industry is Next generation sequencing (NGS) [113]. Chemical analysis from NGS helps food producers quickly identify potential microbial intrusion or other quality threat providing a faster alternative to traditional microbiological approaches [114]. Novel food testing methods, such as DNA-based technique, can improve the efficiencies of laboratories, as they distinct from conventional testing modes. In food production, electrical nose increases safety by providing real-time identification of contaminants or spoilage indicators, while productivity and product quality [115] Fig. 6.

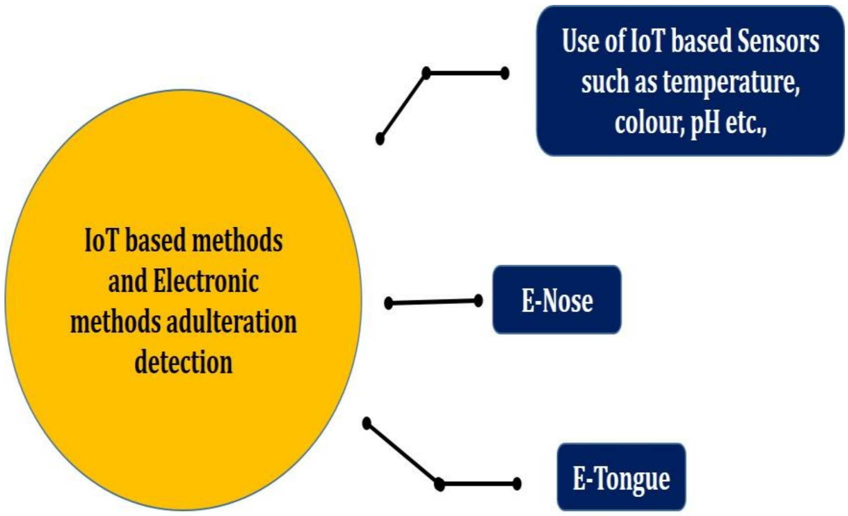

Fig. 6. IoT based methods and electronic adulteration detection

2.7 Launching new product

The introduction of new products into any production unit requires a considerable and cumbersome process. In food industry, success of a new product greatly depends on the consumer's interest [116]. For a new product, it is necessary to get some information about customers and their decision-making through various decision systems [117]. Such data has been instrumental when it comes to decision making of new product development and the overall product launch strategies through the application of artificial intelligence and machine learning algorithms [118]. AI supports essential inquiries, for example "What do customers want?" by analysis of the consumer database, AI can identify trends and predict demand in specific markets [119]. Machine learning helps to process large amounts of consumer's data and make decisions as quickly as consumers can approve them. With the aid of AI, the decision making process has become easier, while also improve the accuracy of predictions, thus helping to launch products successfully in the market [49,92]. In todays the food industry, AI and other advancements in the field of machine learning are effectively applied to new product creation and market development [120]. AI systems are also capable of identifying consumer's sentiment or a current trend that would enable companies to make the right decisions when it comes to product formulations, packaging and even marketing strategies [121]. Unlike the conventional approach that relied on case analysis or surveys with relatively low efficiency, AI and ML provide much more accurate and innovative approaches for introduce the food products to the market [113].

2.8 Management of Supply chain

Currently the most promising technologies supporting Internet of Things (IoT) in supply chains include Wireless Sensor Networks (WSN) and Radio Frequency Identification (RFID). The RFID system uses radio waves to capture and recognize entities in order to improve the way businesses conduct their operations. The deployment of RFID and WSN enhances warehouse operations and management, enhancing productivity [122,123]. RFID systems enable real-time monitoring of the flow and status of goods within the supply chain, as a result increasing its efficiency and productivity.

Wireless sensor technology, also known as sensors play crucial role in data acquisition, monitoring and measurement across various applications [124]. These sensors allow uninterrupted continuous monitoring of the products, from their creation all through to delivery, thus increasing resource use efficiency, and reducing losses. When integrating into such systems, inventory, pricing, and demand measurement can be controlled and optimized, supporting more efficient operations [125].

Properly utilizing AI is of paramount importance for supply chain management, particularly for activities such as forecasting, inventory management, and continuous controlling and monitoring of goods throughout their supply chain lifecycle [125–127]. Other systems such as Symphony Retail's AI-powered technology, offer real-time benefits for the transportation bookings, billing, and inventory management, helping to shorten the decision-making and operational timeliness [128].

2.9 Meat Processing

AI is becoming central to implementing adaptable response in meat processing and production lines, which differ from one carcass and suboptimal cut to another [129]. AI can be applied to a number of aspects of food processing that require intelligent decision-making such as determining which subprimals need sorting, or which portions of the meat need to be trimmed of surface fat. AI has certainly improve decision-making in automated production systems, ensuring that production meets required standards, and the right products get delivered to the right customer [130–132]. Through intelligent systems, quality control is more easily achieved, ensuring that only high-quality products are marketed to consumer.

In meat processing, three main factors namely, spoilage, contamination and quality can cause significant issues for the safety and quality of meat products [133]. Conventional approaches to identifying spoilage or contamination, such as immunological and nucleic acid techniques, are lengthy and cumbersome processes [134]. As a result, AI and machine learning algorithms are slowly incorporated into food safety approaches to improve identification outcomes. Recent developments have focused more on biochemical methods, including biosensors, electronic noses, and infrared spectroscopy combined with artificial neural networks (ANNs) and genetic algorithms [135]. These AI-driven techniques provide quicker, contactless, and more precise ways of identifying/detecting spoilage and contamination, leading to quicker results and reducing the risk of foodborne illness.

3. Challenges of AI in Food Production and Supply Chain

AI has also demonstrated a lot of promise in various sub-sectors of food production, addressing issues such as crop management, food waste and supply chain distribution [136]. Cameras and drones within AI systems are used to monitor variations on water and fertilizer use, increase crop production, and identify threats which then triggers an alarm [8,137–141]. Moreover, AI helps to reduce food wastage across all production fields by ensuring accurate item tracking and evaluation of nutritional value particularly in the restaurant and food services industries [142]. However, developing such reliable AI systems for these applications is not without its challenges.

Private label food producers face one major concern, measuring the nanomaterials present in food to ensure safety and compliance with current food laws [143,144]. Further development in this area is crucial to understanding the potential risks and benefits of nanomaterials in food [145,146]. Despite these challenges, there is latent potential for cost-effective and efficient fruit harvesting in suboptimal environments, for example, by robotization to replace costly manual labor [147–149]. However, the key challenges remain in the effective use of machine learning algorithms and sensors under dynamic conditions [150,151].

In supply chain management, the information technology has been widely involved in managing varying demands, food hygiene requirement, and potential future needs [152,153]. Even though AI has proven to significantly enhance the functionality of numerous supply chain processes, it remain challenging to implement these technologies in certain areas, such as inconsistent supplies and stringently regulated food safety standards/norms [154,155]. Another critical issue is the predictability of food spoilage, where sensors could possibly minimize food wastage and reduce the incidence of food-borne diseases. However, developing precise sensor technologies that can accurately detect spoilage within packaging is still in the experimental stages and a long way from widespread application [156–159].

4. Conclusion

Currently, artificial intelligence is primarily used at the basic level in the food industry, with key application in waste management, sanitation, and food safety. This paper has highlighted that the deployment of AI is poised to expand its influence in the food processing industry, resulting in better and cost-effective production in line with the broader health goal of individuals, communities and societies. Pressure on food and agriculture elements is increasing due to factors such as population growth, climate changes, depletion of the natural resources, and advance in technology, all of which calls for the use of digital technologies. With AI, use of machine learning tools, sensors, satellite data and automation, these technologies should be used right from the farm gate to the consumer’s table. For instance, these technologies can significantly improve crop surveillance, mechanization of farm equipment, and tracking of agro-food commodities ensuring efficient food production lines and supply chain, particularly in agricultural foods. AI algorithms, in particular, are already demonstrating great potential in increasing the efficiency of food processing and enhancing the quality of the final product. In this study, the application of AI in the agricultural supply chain shows its capability/ability to tackle/address existing issues and its diversification into food processing technologies. In a bid to increase the efficiency and effectiveness of food production and processing, it is expected that AI and other related technologies will become integrated throughout the food value chain. It is now increasingly important to understand how this shift will positively impact productivity and promote sustainable and healthy food to feed the growing global population.

References

[1]. D. Mhlanga, Human-Centered Artificial Intelligence: The Superlative Approach to Achieve Sustainable Development Goals in the Fourth Industrial Revolution, Sustainability, 14 (2022).

[2]. W.P. Falcon, R.L. Naylor, N.D. Shankar, Rethinking global food demand for 2050, Population and Development Review, 48 (2022) 921–957.

[3]. X. Tian, B.A. Engel, H. Qian, E. Hua, S. Sun, Y. Wang, Will reaching the maximum achievable yield potential meet future global food demand?, Journal of Cleaner Production, 294 (2021) 126285.

[4]. M. Van Dijk, T. Morley, M.L. Rau, Y. Saghai, A meta-analysis of projected global food demand and population at risk of hunger for the period 2010--2050, Nature Food, 2 (2021) 494–501.

R. Ben Ayed, M. Hanana, Artificial Intelligence to Improve the Food and Agriculture Sector. 2021. Journal of Food Quality. (2021) 5584754.

[5]. A. Krivohlavek, Food Safety, Standards and Norms Against Bioterrorism: Food Safety and Hazards BT - Defence Against Bioterrorism, in: V. Radosavljevic, I. Banjari, G. Belojevic (Eds.), Springer Netherlands. 2018. Dordrecht. : pp. 239–248.

[6]. T. Bidyalakshmi, B. Jyoti, S.M. Mansuri, A. Srivastava, D. Mohapatra, Y.B. Kalnar, K. Narsaiah, N. Indore, Application of Artificial Intelligence in Food Processing: Current Status and Future Prospects, Food Engineering Reviews, (2024).

[7]. H. Ding, J. Tian, W. Yu, D.I. Wilson, B.R. Young, X. Cui, X. Xin, Z. Wang, W. Li, The Application of Artificial Intelligence and Big Data in the Food Industry, Foods, 12 (2023).

[8]. V. Zatsu, A.E. Shine, J.M. Tharakan, D. Peter, T.V. Ranganathan, S.S. Alotaibi, R. Mugabi, A. Bin Muhsinah, M. Waseem, G.A. Nayik, Revolutionizing the food industry: The transformative power of artificial intelligence-a review, Food Chemistry: X, 24 (2024) 101867.

[9]. B. Das, A. Hoque, S. Roy, K. Kumar, A.A. Laskar, A.S. Mazumder, Post-Harvest Technologies and Automation: Al-Driven Innovations in Food Processing and Supply Chains, (2025).

[10]. D. Wang, M. Zhang, M. Li, J. Lin, Fruits and vegetables preservation based on AI technology: Research progress and application prospects, Computers and Electronics in Agriculture, 226 (2024) 109382.

[11]. M. Daheriya, D.K. Verma, E.K. Kuruba, K.C. Mahajan, N.U. Joshi, Advances in multi-fruit and vegetable grading: a comprehensive review, International Journal of Environment and Climate Change, 13 (2023) 1239–1245.

[12]. Y. Yun, Z. Ma, X. An, D. Li, On-Site Intelligent Grading System for Fruits and Vegetables: Case Studies on Tomato and Apple BT - Advanced Sensing and Robotics Technologies in Smart Agriculture, in: Y. Yun, W. Sheng, Z. Zhang (Eds.), Springer Nature Singapore. 2024. Singapore. : pp. 61–85.

[13]. J. Yu, Z. Zhang, Y. Li, W. Hua, X. Wei, C. Igathinathane, M. Mhamed, W. Zhang, X. Jiao, L. Yang, M. Zhang, H. Li, In-field grading and sorting technology of apples: A state-of-the-art review, Computers and Electronics in Agriculture, 226 (2024) 109383.

[14]. S. Getahun, H. Kefale, Y. Gelaye, Application of precision agriculture technologies for sustainable crop production and environmental sustainability: A systematic review. 2024. The Scientific World Journal. (2024) 2126734.

[15]. G. Mohyuddin, M.A. Khan, A. Haseeb, S. Mahpara, M. Waseem, A.M. Saleh, Evaluation of Machine Learning Approaches for Precision Farming in Smart Agriculture System: A Comprehensive Review, IEEE Access, 12 (2024) 60155–60184.

[16]. O.B. Akintuyi, Adaptive AI in precision agriculture: a review: investigating the use of self-learning algorithms in optimizing farm operations based on real-time data, Research Journal of Multidisciplinary Studies, 7 (2024) 16–30.
[17]. E.M.B.M. Karunathilake, A.T. Le, S. Heo, Y.S. Chung, S. Mansoor, The Path to Smart Farming: Innovations and Opportunities in Precision Agriculture, Agriculture, 13 (2023).
[18]. T. Ayoub Shaikh, T. Rasool, F. Rasheed Lone, Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming, Computers and Electronics in Agriculture, 198 (2022) 107119.
[19]. Z.A. Ali, M. Zain, M.S. Pathan, P. Mooney, Contributions of artificial intelligence for circular economy transition leading toward sustainability: an explorative study in agriculture and food industries of Pakistan, Environment, Development and Sustainability, 26 (2024) 19131–19175.
[20]. E. Sánchez-García, J. Martínez-Falcó, B. Marco-Lajara, E. Manresa-Marhuenda, Revolutionizing the circular economy through new technologies: A new era of sustainable progress, Environmental Technology & Innovation, 33 (2024) 103509.
[21]. A. Soo, L. Gao, H.K. Shon, Machine learning framework for wastewater circular economy — Towards smarter nutrient recoveries, Desalination, 592 (2024) 118092.
[22]. K.Y. Lin, S.H. Wei, Advancing the industrial circular economy: the integrative role of machine learning in resource optimization, Journal of Green Economy and Low-Carbon Development, 2 (2023) 122–136.
[23]. H. Onyeaka, P. Tamasiga, U.M. Nwauzoma, T. Miri, U.C. Juliet, O. Nwaiwu, A.A. Akinsemolu, Using artificial intelligence to tackle food waste and enhance the circular economy: Maximising resource efficiency and Minimising environmental impact: A review, Sustainability, 15 (2023) 10482.
[24]. Noman, U.H. Akter, T.H. Pranto, A.K.M.B. Haque, Machine Learning and Artificial Intelligence in Circular Economy: A Bibliometric Analysis and Systematic Literature Review, Annals of Emerging Technologies in Computing, 6 (2022) 13–40.
[25]. I. Palomares, E. Martínez-Cámara, R. Montes, P. García-Moral, M. Chiachio, J. Chiachio, S. Alonso, F.J. Melero, D. Molina, B. Fernández, C. Moral, R. Marchena, J.P. de Vargas, F. Herrera, A panoramic view and swot analysis of artificial intelligence for achieving the sustainable development goals by 2030: progress and prospects, Applied Intelligence, 51 (2021) 6497–6527.
[26]. D. Laborde, W. Martin, J. Swinnen, R. Vos, COVID-19 risks to global food security, Science, 369 (2020) 500–502.
[27]. A. Hassoun, S. Jagtap, H. Trollman, G. Garcia-Garcia, L.N.K. Duong, P. Saxena, Y. Bouzembrak, H. Treiblmaier, C. Para-López, C. Carmona-Torres, K. Dev, D. Mhlanga, A. Aït-Kaddour, From Food Industry 40 to Food Industry 50: Identifying technological enablers and potential future applications in the food sector, Comprehensive Reviews in Food Science and Food Safety, 23 (2024) e370040.
[28]. M. Padhiary, J.A. Barbhuiya, D. Roy, P. Roy, 3D printing applications in smart farming and food processing, Smart Agricultural Technology, 9 (2024) 100553.
[29]. D. Raheem, H. Treiblmaier, W.M. Mohammed, B.R. Ferrer, J.L. Martinez-Lastra, Chapter 7 - Robotics as key enabler technology in Food Industry 40 and beyond, in: A.B.T.-F.I. 4. . Hassoun (Ed.), Developments in Food Quality and Safety. 2024. Academic Press. : pp. 121–131.
[30]. A. Rejeb, A. Abdollahi, K. Rejeb, G.J. Keogh, Smart Logistics for Sustainable Food Industries, in: Smart Food Industry: The Blockchain for Sustainable Engineering, CRC Press. 2023. Boca Raton. : pp. 292–306.
[31]. G. Tsaramirsis, A. Kantaros, I. Al-Darraji, D. Piromalis, C. Apostolopoulos, A. Pavlopoulou, M. Alrammal, Z. Ismail, S.M. Buhari, M. Stojmenovic, H. Tamimi, P. Randhawa, A. Patel, F.Q. Khan, A Modern Approach towards an Industry 40 Model: From Driving Technologies to Management. 2022. Journal of Sensors. (2022) 5023011.
[32]. S. Bag, J.H.C. Pretorius, S. Gupta, Y.K. Dwivedi, Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities, Technological Forecasting and Social Change, 163 (2021) 120420.
[33]. A. Nayyar, A. Kumar, A roadmap to industry 40: Smart production, sharp business and sustainable development. 2019. Springer. .

[34]. I. Kumar, J. Rawat, N. Mohd, S. Husain, Opportunities of artificial intelligence and machine learning in the food industry. 2021. Journal of Food Quality. (2021) 4535567.

[35]. T. Liberty, E. Habanabakize, P.I. Adamu, S.M. Bata, Advancing food manufacturing: Leveraging robotic solutions for enhanced quality assurance and traceability across global supply networks, Trends in Science & Technology, 153 (2024) 104705.

[36]. W. Min, P. Zhou, L. Xu, T. Liu, T. Li, M. Huang, Y. Jin, Y. Yi, M. Wen, S. Jiang, R. Jain, From Plate to Production: Artificial Intelligence in Modern Consumer-Driven Food Systems, (2023).

[37]. M.R. Islam, M.Z.H. Zamil, M.E. Rayed, M.M. Kabir, M.F. Mridha, S. Nishimura, J. Shin, Deep Learning and Computer Vision Techniques for Enhanced Quality Control in Manufacturing Processes, IEEE Access, (2024).

[38]. G. Chryssolouris, K. Alexopoulos, Z. Arkouli, Artificial intelligence in manufacturing systems, in: A Perspective on Artificial Intelligence in Manufacturing. 2023. Springer. : pp. 79–135.

[39]. M. Del Gallo, G. Mazzuto, F.E. Ciarapica, M. Bevilacqua, Artificial Intelligence to Solve Production Schedulig Problems in Real Industrial Settings: Systematic Literature Review, Electronics, 12 (023).

[40]. R. Manne, S.C. Kantheti, Green IoT Towards Environmentally Friendly, Sustainable and Revolutionized Farming. 2021. in: Green Internet of Things and Machine Learning. : pp. 113–139.

[41]. M. Ghobakhloo, M. Fathi, Industry 40 and opportunities for energy sustainability, Journal of Cleaner Production, 295 (2021) 126427.

[42]. Oláh, N. Aburumman, J. Popp, M.A. Khan, H. Haddad, N. Kitukutha, Impact of Industry 40 on environmental sustainability, Sustainability, 12 (2020) 4674.

[43]. F. Sunmola, G. Baryannis, A. Tan, K. Co, E. Papadakis, Holistic Framework for Blockchain-Based Halal Compliance in Supply Chains Enabled by Artificial Intelligence, Systems, 13 (2025).

[44]. D. Patel, C.K. Sahu, R. Rai, Security in modern manufacturing systems: integrating blockchain in artificial intelligence-assisted manufacturing, International Journal of Production Research, 62 (2024) 1041–1071.

[45]. J.L. Vilas-Boas, J.J.P.C. Rodrigues, A.M. Alberti, Convergence of Distributed Ledger Technologies with Digital Twins, IoT, and AI for fresh food logistics: Challenges and opportunities, Journal of Industrial Information Integration, 31 (2023) 100393.

[46]. N. Eyo-Udo, Leveraging artificial intelligence for enhanced supply chain optimization, Open Access Research Journal of Multidisciplinary Studies, 7 (2024) 1–15.

[47]. S.A. Bhat, N.-F. Huang, Big data and ai revolution in precision agriculture: Survey and challenges, Ieee Access, 9 (2021) 110209–110222.

[48]. A. Haleem, M. Javaid, M. Asim Qadri, R. Pratap Singh, R. Suman, Artificial intelligence (AI) applications for marketing: A literature-based study, International Journal of Intelligent Networks, 3 (2022) 119–132.

[49]. A. Caratti, F. Trapani, A. Fina, C. Bicchi, E. Liberto, E.R. Stephen, Q. Tao, D. Geschwender, C. Cordero, others, Boosting comprehensive two-dimensional gas chromatography with Artificial Intelligence: Computer Vision helps to see what we smell. 2024. in: Abstract Book. : pp. 7–8.

[50]. M. Addanki, P. Patra, P. Kandra, Recent advances and applications of artificial intelligence and related technologies in the food industry, Applied Food Research, 2 (2022) 100126.

[51]. G.V.S. Bhagya Raj, K.K. Dash, Comprehensive study on applications of artificial neural network in food process modeling, Critical Reviews in Food Science and Nutrition, 62 (2022) 2756–2783.

[52]. J. Nayak, K. Vakula, P. Dinesh, B. Naik, D. Pelusi, Intelligent food processing: Journey from artificial neural network to deep learning, Computer Science Review, 38 (2020) 100297.

[53]. G. Tayfur, Soft computing in water resources engineering: Artificial neural networks, fuzzy logic and genetic algorithms. 2014. WIT Press. .

[54]. A. Agrawal, J. Gans, A. Goldfarb, Prediction Machines, Updated and Expanded: The Simple Economics of Artificial Intelligence. 2022. Harvard Business Press. .

[55]. A. Aijaz, Revolutionizing Bakeries with Artificial Intelligence: A Sweet Blend of Innovation, in: Artificial Intelligence in the Food Industry. 2025. CRC Press. : pp. 153–170.

[56]. X. Wang, Managing Land Carrying Capacity: Key to Achieving Sustainable Production Systems for Food Security, Land, 11 (2022).

[57]. A. Hossain, T.J. Krupnik, J. Timsina, M.G. Mahboob, A.K. Chaki, M. Farooq, R. Bhatt, S. Fahad, M. Hasanuzzaman, Agricultural Land Degradation: Processes and Problems Undermining Future Food Security BT - Environment, Climate, Plant and Vegetation Growth, in: S. Fahad, M. Hasanuzzaman, M. Alam, H. Ullah, M. Saeed, I. Ali Khan, M. Adnan (Eds.), Springer International Publishing. 2020. Cham. : pp. 17–61.

[58]. F. Enayaty-Ahangar, S.I. Murphy, N.H. Martin, M. Wiedmann, R. Ivanek, Optimizing pasteurized fluid milk shelf-life through microbial spoilage reduction, Frontiers in Sustainable Food Systems, 5 (2021) 670029.

[59]. K.C. Anirudh, M. Dixit, S. Karat, Exploring the Applications of Wireless Sensor Networks and the Internet of Things in Agricultural and Livestock Production and Management, in: Emerging Technologies and the Application of WSN and IoT. 2024. CRC Press. : pp. 209–227.

[60]. A. Ali, M. Ataei Kachouei, A. Kaushik, Internet of Things-Enabled Food and Plant Sensors to Empower Sustainability, (2023).

[61]. M. Gaworski, Implementation of technical and technological progress in dairy production, Processes, 9 (2021) 2103.

[62]. L.M.S. Filho, M.A. Lopes, S.C. Brito, G. Rossi, L. Conti, M. Barbari, Robotic milking of dairy cows: A review, Semina:Ciencias Agrarias, 41 (2020) 2833–2849.

[63]. J.A. Hogenboom, L. Pellegrino, A. Sandrucci, V. Rosi, P. D'Incecco, Invited review: Hygienic quality, composition, and technological performance of raw milk obtained by robotic milking of cows, Journal of Dairy Science, 102 (2019) 7640–7654.

[64]. S. Bhoj, A. Tarafdar, M. Singh, G.K. Gaur, Smart and Automatic Milking Systems: Benefits and Prospects BT - Smart and Sustainable Food Technologies, in: S. Sehgal, B. Singh, V. Sharma (Eds.), Springer Nature Singapore. 2022. Singapore. : pp. 87–121.

[65]. L.E. Davis, Impact of Housing and Management on Production, Behavior, and Welfare of Dairy Cows in Automatic Milking Systems, (2022).

[66]. A. de la Hoz, P. Caripán, B. Moltedo, N. Ferrada, R.A. Contreras, A metabolomic approach of AI-driven enzymatic digestion of pumpkin seed flour for producing umami metabolites, International Journal of Gastronomy and Food Science, 39 (2025) 101117.

[67]. I.A.A. Abou Ayana, M.R. Elgarhy, F.O. Al-Otibi, M.M. Omar, M.Z. El-Abbassy, S.A. Khalifa, Y.A. Helmy, W.I.A. Saber, Artificial Intelligence-Powered Optimization and Milk Permeate Upcycling for Innovative Sesame Milk with Enhanced Probiotic Viability and Sensory Appeal, ACS Omega, 9 (2024) 25189–25202.

[68]. H.T. Gorji, S.M. Shahabi, A. Sharma, L.Q. Tande, K. Husarik, J. Qin, D.E. Chan, I. Baek, M.S. Kim, N. MacKinnon, J. Morrow, S. Sokolov, A. Akhbardeh, F. Vasefi, K. Tavakolian, Combining deep learning and fluorescence imaging to automatically identify fecal contamination on meat carcasses, Scientific Reports, 12 (2022) 1–11.

[69]. R. Versini, S. Sritharan, B. Aykac Fas, T. Tubiana, S.Z. Aimeur, J. Henri, M. Erard, O. Nüsse, J. Andreani, M. Baaden, P. Fuchs, T. Galochkina, A. Chatzigoulas, Z. Cournia, H. Santuz, S. Sacquin-Mora, A. Taly, A Perspective on the Prospective Use of AI in Protein Structure Prediction, Journal of Chemical Information and Modeling, 64 (2024) 26–41.

[70]. K. Agrawal, P. Goktas, M. Holtkemper, C. Beecks, N. Kumar, AI-driven transformation in food manufacturing: a pathway to sustainable efficiency and quality assurance, Frontiers in Nutrition, 12 (2025).

[71]. K. Przybył, K. Koszela, Applications MLP and Other Methods in Artificial Intelligence of Fruit and Vegetable in Convective and Spray Drying, Applied Sciences, 13 (2023).

[72]. C.K.W. Lee, Y. Xu, Q. Yuan, Y.H. Chan, W.Y. Poon, H. Zhong, S. Chen, M.G. Li, Advanced 3D Food Printing with Simultaneous Cooking and Generative AI Design, Advanced Materials, n/a (2025) 2408282.

[73]. R. Dhar, P.P. Bhalerao, S. Chakraborty, Formulation of a mixed fruit beverage using fuzzy logic optimization of sensory data and designing its batch thermal pasteurization process, Journal of Food Science, 86 (2021) 463–474.

[74]. K. Shehzad, Technology Predictive AI Models for Food Spoilage and Shelf-Life Estimation, Global Trends in Science and Technology, 1 (2025) 75–94.

[75]. Y.B. Wakchaure, B.K. Patle, S. Pawar, Prospects of robotics in food processing: an overview, Journal of Mechanical Engineering, Automation and Control Systems, 4 (2023) 17–37.

[76]. C. Gabellieri, The role of interaction forces in robotic manipulation for logistics: a special focus on depalletizing and object delivery, (2021).

[77]. M.T. Ahmed, O. Monjur, A. Khaliduzzaman, M. Kamruzzaman, A comprehensive review of deep learning-based hyperspectral image reconstruction for agri-food quality appraisal, Artificial Intelligence Review, 58 (2025) 96.

[78]. Z. Muftah, K. Abdusalam, A. Abdusalam, Optimizing Quality Control : A Comprehensive Analysis of Computer Vision Methods for Assessing Vegetables and Fruits, 37 (2024) 101–114.

[79]. T. Zhang, K. Li, X. Chen, C. Zhong, B. Luo, I. Grijalva, B. McCornack, D. Flippo, A. Sharda, G. Wang, Aphid cluster recognition and detection in the wild using deep learning models, Scientific Reports, 13 (2023) 13410.

[80]. M. Soori, F.K.G. Jough, R. Dastres, B. Arezoo, AI-Based Decision Support Systems in Industry 40, A Review, Journal of Economy and Technology, (2024).

[81]. A. Mishra, S. Chaudhari, C. Singh, U.P. Indian, Sorting Machine for Fruits and Vegetables for Agricultural Advancements using IoT, 1 (2024) 40–48.

[82]. S. Vasudevan, M.L. Mekhalfi, C. Blanes, M. Lecca, F. Poiesi, P.I. Chippendale, P.M. Fresnillo, W.M. Mohammed, J.L.M. Lastra, Robotics and Machine Vision for Primary Food Manipulation and Packaging: A Survey, IEEE Access, (2024).

[83]. A. Aghababaei, F. Aghababaei, M. Pignitter, M. Hadidi, Artificial Intelligence in Agro-Food Systems: From Farm to Fork, Foods, 14 (2025).

[84]. A. Aladhadh, A Probabilistic Understanding of Computational Complexity, a Singularity Theory Approach. 2023. in: 2023 16th International Conference on Developments in ESystems Engineering (DeSE). : pp. 24–29.

[85]. H. Imanian, A. Mohammadian, V. Farhangmehr, P. Payeur, D. Goodarzi, J. Hiedra Cobo, H. Shirkhani, A comparative analysis of deep learning models for soil temperature prediction in cold climates, Theoretical and Applied Climatology, 155 (2024) 2571–2587.

[86]. L. Ferrone, F.M. Zanzotto, Symbolic, distributed, and distributional representations for natural language processing in the era of deep learning: A survey, Frontiers in Robotics and AI, 6 (2020) 153.

[87]. E. Khamoushi, AI in Food Marketing from Personalized Recommendations to Predictive Analytics: Comparing Traditional Advertising Techniques with AI-Driven Strategies, (2024).

[88]. R. Raj, D.S. Gondi, S.R. Nitnaware, S. Banerjee, S. Athithan, Arpita, Remote Sensing--Based Food Processing for Changing Climatic Conditions, Remote Sensing in Earth Systems Sciences, (2025) 1–12.

[89]. S. Adhikari, B.R. McFadden, Bridging taste and health: the role of machine learning in consumer food selection, International Food and Agribusiness Management Review, 1 (2025) 1–16.

[90]. R. Gulati, M. Bhagat, Content and knowledge based food recommending intelligence enabled system (FRIES). 2021. in: 2021 5th International Conference on Computing Methodologies and Communication (ICCMC). : pp. 1743–1749.

[91]. O. Badmus, S.A. Rajput, J.B. Arogundade, M. Williams, AI-driven business analytics and decision making, World Journal of Advanced Research and Reviews, 24 (2024) 616–633.

[92]. D. Ajiga, P.A. Okeleke, S.O. Folorunsho, C. Ezeigweneme, Enhancing software development prices with AI insights in high-tech companies, IEEE Software Engineering Institute, Technical Report TR-2024-003, (2024).

[93]. P. PraveenaSri, V.N.P. Prasuna, M.N. Shilpa, K. Purushotham Prasad, S. Asma Begum, R. Murugesan, Machine Learning and IoT Driven Precision Agriculture for Indian Crop Selection. 2024. in: International Conference Summit on Artificial Intelligence. : pp. 221–237.

[94]. I. Zahoor, S.A. Wani, T.A. Ganaie, Artificial Intelligence in the Food Industry: Enhancing Quality and Safety. 2025. CRC Press. .
[95]. S. Konur, Y. Lan, D. Thakker, G. Morkyani, N. Polovina, J. Sharp, Towards design and implementation of Industry 40 for food manufacturing, Neural Computing and Applications, (2023) 1–13.
[96]. C. Axel, E. Zannini, E.K. Arendt, Mold spoilage of bread and its biopreservation: A review of current strategies for bread shelf life extension, Critical Reviews in Food Science and Nutrition, 57 (2017) 3528–3542.
[97]. D. Selişteanu, M. Roman, D. Şendrescu, E. Petre, B. Popa, A distributed control system for processes in food industry: Architecture and implementation. 2018. in: 2018 19th International Carpathian Control Conference (ICCC). : pp. 128–133.
[98]. R.J. González, E. Pastor Cavada, J. Vioque Peña, R.L. Torres, D.M. De Greef, S.R. Drago, Extrusion Conditions and Amylose Content Affect Physicochemical Properties of Extrudates Obtained from Brown Rice Grains. 2013. International Journal of Food Science. (2013) 584148.
[99]. M. Modesti, A. Tonacci, F. Sansone, L. Billeci, A. Bellincontro, G. Cacopardo, C. Sanmartin, I. Taglieri, F. Venturi, E-senses, panel tests and wearable sensors: a teamwork for food quality assessment and prediction of consumer's choices, Chemosensors, 10 (2022) 244.
[100]. J. Rahimi, J. Baur, A. Singh, Digital imaging as a tool to study the structure of porous baked foods, Journal of Cereal Science, 95 (2020) 103084.
[101]. L. Issabekova, I. Utepbergenov, S. Toybayeva, K. Makulov, others, Temperature and Humidity Control System Based on Baking Ovens Using Fuzzy Logic. 2023. in: 2023 IEEE International Conference on Smart Information Systems and Technologies (SIST). : pp. 573–578.
[102]. S. Otles, A. Sakalli, 15 - Industry 40: The Smart Factory of the Future in Beverage Industry, in: A.M. Grumezescu, A.M.B.T.-P. and M. of B. Holban (Eds.). 2019. Woodhead Publishing. : pp. 439–469.
[103]. W.S. Ayoub, R. Tariq, S. Farooq, I. Zahoor, Artificial Intelligence in Beverages, in: Artificial Intelligence in the Food Industry. 2025. CRC Press. : pp. 116–133.
[104]. D. Lavorato, P. Piedepalumbo, How Smart Technologies Affect the Decision-Making and Control System of Food and Beverage Companies—A Case Study, Sustainability, 15 (2023).
[105]. H. Abi-Rizk, D. Jouan-Rimbaud Bouveresse, J. Chamberland, C.B.Y. Cordella, Recent developments of e-sensing devices coupled to data processing techniques in food quality evaluation: a critical review, Anal. Methods, 15 (2023) 5410–5440.
[106]. P.E.S. Munekata, S. Finardi, C.K. de Souza, C. Meinert, M. Pateiro, T.G. Hoffmann, R. Domínguez, S.L. Bertoli, M. Kumar, J.M. Lorenzo, Applications of Electronic Nose, Electronic Eye and Electronic Tongue in Quality, Safety and Shelf Life of Meat and Meat Products: A Review, Sensors, 23 (2023).
[107]. K. Goyal, P. Kumar, K. Verma, Food Adulteration Detection using Artificial Intelligence: A Systematic Review, Archives of Computational Methods in Engineering, 29 (2022) 397–426.
[108]. H.A. Selmy, H.K. Mohamed, W. Medhat, A predictive analytics framework for sensor data using time series and deep learning techniques, Neural Computing and Applications, 36 (2024) 6119–6132.
[109]. A. Izquierdo-Yusta, M.D. Méndez-Aparicio, A.I. Jiménez-Zarco, M.P. Mart\'\inez-Ru\'\iz, When responsible production and consumption matter: The case of Danone, in: Responsible Consumption and Sustainability: Case Studies from Corporate Social Responsibility, Social Marketing, and Behavioral Economics. 2023. Springer. : pp. 199–211.
[110]. X. Deng, S. Cao, A.L. Horn, Emerging Applications of Machine Learning in Food Safety, Annual Review of Food Science and Technology, 12 (2021) 513–538.
[111]. L. Lu, Z. Hu, X. Hu, D. Li, S. Tian, Electronic tongue and electronic nose for food quality and safety, Food Research International, 162 (2022) 112214.
[112]. M. Choudhary, P. Kaur, Integrating AI with Machine Learning (ML) for Real-Time Detection in Food Industry, in: Artificial Intelligence in the Food Industry. 2025. CRC Press. : pp. 297–315.
[113]. A.N. Alsharksi, S. Sirekbasan, T. Gürkök-Tan, A. Mustapha, From Tradition to Innovation: Diverse Molecular Techniques in the Fight Against Infectious Diseases, Diagnostics, 14 (2024).
[114]. E. Poeta, A. Liboà, S. Mistrali, E. Núñez-Carmona, V. Sberveglieri, Nanotechnology and E-Sensing for Food Chain Quality and Safety, Sensors, 23 (2023).

[115]. R.P.F. Guiné, S.G. Florença, M.J. Barroca, O. Anjos, The Link between the Consumer and the Innovations in Food Product Development, Foods, 9 (2020).

[116]. M. Abdel-Basset, M. Mohamed, V. Chang, F. Smarandache, IoT and Its Impact on the Electronics Market: A Powerful Decision Support System for Helping Customers in Choosing the Best Product, Symmetry, 11 (2019).

[117]. Angelica Marrone. 2022. Optimizing Product Development and Innovation Processes with Artificial Intelligence. .

[118]. L. Rainsberger, Benefits: What AI Can Do for Sales, in: AI-The New Intelligence in Sales: Tools, Applications and Potentials of Artificial Intelligence. 2022. Springer. : pp. 17–34.

[119]. V. Kakani, V.H. Nguyen, B.P. Kumar, H. Kim, V.R. Pasupuleti, A critical review on computer vision and artificial intelligence in food industry, Journal of Agriculture and Food Research, 2 (2020) 100033.

[120]. P.A. Okeleke, D. Ajiga, S.O. Folorunsho, C. Ezeigweneme, Predictive analytics for market trends using AI: A study in consumer behavior, International Journal of Engineering Research Updates, 7 (2024) 36–49.

[121]. B. Unhelkar, S. Joshi, M. Sharma, S. Prakash, A.K. Mani, M. Prasad, Enhancing supply chain performance using RFID technology and decision support systems in the industry 40–A systematic literature review, International Journal of Information Management Data Insights, 2 (2022) 100084.

[122]. W.C. Tan, M.S. Sidhu, Review of RFID and IoT integration in supply chain management, Operations Research Perspectives, 9 (2022) 100229.

[123]. M. Ben-Daya, E. Hassini, Z. Bahroun, B.H. Banimfreg, The role of internet of things in food supply chain quality management: A review, Quality Management Journal, 28 (2020) 17–40.

[124]. V. Pasupuleti, B. Thuraka, C.S. Kodete, S. Malisetty, Enhancing Supply Chain Agility and Sustainability through Machine Learning: Optimization Techniques for Logistics and Inventory Management, Logistics, 8 (2024).

[125]. D.K. Vaka, Integrating inventory management and distribution: A holistic supply chain strategy, The International Journal of Managing Value and Supply Chains, 15 (2024) 13–23.

[126]. P. Helo, Y. Hao, Artificial intelligence in operations management and supply chain management: an exploratory case study, Production Planning & Control, 33 (2022) 1573–1590.

[127]. R. Smith, M. Cubino, E. McKeon, The AI Revolution in Customer Service and Support: A Practical Guide to Impactful Deployment of AI to Best Serve Your Customers. 2024. Pearson Education. .

[128]. S. Davoudi, P. Stasinopoulos, N. Shiwakoti, Two Decades of Advancements in Cold Supply Chain Logistics for Reducing Food Waste: A Review with Focus on the Meat Industry, Sustainability, 16 (2024).

[129]. J. Rugji, Z. Erol, F. Taşçı, L. Musa, A. Hamadani, M.G. Gündemir, E. Karalliu, S.A. Siddiqui, Utilization of AI – reshaping the future of food safety, agriculture and food security – a critical review. n.d.. Critical Reviews in Food Science and Nutrition. 1–45.

[130]. R. Barthwal, D. Kathuria, S. Joshi, R.S.S. Kaler, N. Singh, New trends in the development and application of artificial intelligence in food processing, Innovative Food Science & Emerging Technologies, 92 (2024) 103600.

[131]. R. Vashishth, A.K. Pandey, P. Kaur, A.D. Semwal, Smart technologies in food manufacturing, in: Smart and Sustainable Food Technologies. 2022. Springer. : pp. 125–155.

[132]. A.J. Pellissery, P.G. Vinayamohan, M.A.R. Amalaradjou, K. Venkitanarayanan, Chapter 17 - Spoilage bacteria and meat quality, in: A.K. Biswas, P.K.B.T.-M.Q.A. Mandal (Eds.). 2020. Academic Press. : pp. 307–334.

[133]. S. Panwar, K.S. Duggirala, P. Yadav, N. Debnath, A.K. Yadav, A. Kumar, Advanced diagnostic methods for identification of bacterial foodborne pathogens: contemporary and upcoming challenges, Critical Reviews in Biotechnology, 43 (2023) 982–1000.

[134]. A. Rabehi, H. Helal, D. Zappa, E. Comini, Advancements and Prospects of Electronic Nose in Various Applications: A Comprehensive Review, Applied Sciences, 14 (2024).

[135]. Q.S. Altaf, R. Ksouri, Application of Machine Learning in the Food Industry, in: Artificial Intelligence in the Food Industry. 2025. CRC Press. : pp. 23–55.

[136]. D. Grewal, A. Guha, S.M. Noble, K. Bentley, The food production–consumption chain: Fighting food insecurity, loss, and waste with technology, Journal of the Academy of Marketing Science, 52 (2024) 1412–1430.
[137]. M. Javaid, A. Haleem, I.H. Khan, R. Suman, Understanding the potential applications of Artificial Intelligence in Agriculture Sector, Advanced Agrochem, 2 (2023) 15–30.
[138]. A. Hafeez, M.A. Husain, S.P. Singh, A. Chauhan, M.T. Khan, N. Kumar, A. Chauhan, S.K. Soni, Implementation of drone technology for farm monitoring & pesticide spraying: A review, Information Processing in Agriculture, 10 (2023) 192–203.
[139]. T.P. da Costa, J. Gillespie, X. Cama-Moncunill, S. Ward, J. Condell, R. Ramanathan, F. Murphy, A systematic review of real-time monitoring technologies and its potential application to reduce food loss and waste: Key elements of food supply chains and IoT technologies, Sustainability, 15 (2022) 614.
[140]. T. Talaviya, D. Shah, N. Patel, H. Yagnik, M. Shah, Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides, Artificial Intelligence in Agriculture, 4 (2020) 58–73.
[141]. C. Bux, Conventional and digital technologies for measuring and monitoring food waste in the healthcare foodservice. n.d.. Journal of Foodservice Business Research. 1–23.
[142]. K.D. Grieger, S.F. Hansen, N.P. Mortensen, S. Cates, B. Kowalcyk, International Implications of Labeling Foods Containing Engineered Nanomaterials, Journal of Food Protection, 79 (2016) 830–842.
[143]. H. Stamm, N. Gibson, E. Anklam, Detection of nanomaterials in food and consumer products: bridging the gap from legislation to enforcement, Food Additives & Contaminants: Part A, 29 (2012) 1175–1182.
[144]. H. Onyeaka, P. Passaretti, T. Miri, Z.T. Al-Sharify, The safety of nanomaterials in food production and packaging, Current Research in Food Science, 5 (2022) 763–774.
[145]. C.E. Handford, M. Dean, M. Henchion, M. Spence, C.T. Elliott, K. Campbell, Implications of nanotechnology for the agri-food industry: Opportunities, benefits and risks, Trends in Food Science & Technology, 40 (2014) 226–241.
[146]. [147] G. Kootstra, J. Senden, E. Torta, R. van de Molengraft, H. Bruyninckx, J. Blasco-Ivars, F. Rovira-Más, P. Kurtser, S. Lowry, O. Ringdahl, others, Advances in agri-food robotics. 2024. Burleigh Dodds Science Publishing. .
[147]. U. Bhattarai, Robotic Blossom Thinning System for Tree Fruit Crops. 2023. Washington State University. .
[148]. A. Zahid, M.S. Mahmud, L. He, P. Heinemann, D. Choi, J. Schupp, Technological advancements towards developing a robotic pruner for apple trees: A review, Computers and Electronics in Agriculture, 189 (2021) 106383.
[149]. S. Qiu, H. Zhao, N. Jiang, Z. Wang, L. Liu, Y. An, H. Zhao, X. Miao, R. Liu, G. Fortino, Multi-sensor information fusion based on machine learning for real applications in human activity recognition: State-of-the-art and research challenges, Information Fusion, 80 (2022) 241–265.
[150]. C. Yang, Y. Feng, A. Whinston, Dynamic pricing and information disclosure for fresh produce: An artificial intelligence approach, Production and Operations Management, 31 (2022) 155–171.
[151]. [152] M. Lezoche, J.E. Hernandez, M. del M.E. Alemany Díaz, H. Panetto, J. Kacprzyk, Agri-food 40: A survey of the supply chains and technologies for the future agriculture, Computers in Industry, 117 (2020) 103187.
[152]. M. Ben-Daya, E. Hassini, Z. Bahroun, Internet of things and supply chain management: a literature review, International Journal of Production Research, 57 (2019) 4719–4742.
[153]. A. Krishnan, X. Xu, M.S. Tamayo, A. Mishra, F. Critzer, Impact of chlorine or peracetic acid on inactivation of Salmonella, Escherichia coli, and Listeria monocytogenes in agricultural water, Science of The Total Environment, 885 (2023) 163884.
[154]. B. Nessler, T. Doms, S. Hochreiter, Functional trustworthiness of AI systems by statistically valid testing, ArXiv Preprint ArXiv:2310.02727, (2023).
[155]. Y. Ha, Advancements in gaseous sensor technology for ensuring food safety: a review, International Journal of Food Science and Technology, 60 (2025) vvae026.

[156]. O.R. Taiwo, H. Onyeaka, E.K. Oladipo, J.K. Oloke, D.C. Chukwugozie, Advancements in Predictive Microbiology: Integrating New Technologies for Efficient Food Safety Models. 2024. International Journal of Microbiology. (2024) 6612162.

[157]. N. Joshi, G. Pransu, C. Adam Conte-Junior, Critical review and recent advances of 2D materials-Based gas sensors for food spoilage detection, Critical Reviews in Food Science and Nutrition, 63 (2023) 10536–10559.

[158]. E. Sonwani, U. Bansal, R. Alroobaea, A.M. Baqasah, M. Hedabou, An artificial intelligence approach toward food spoilage detection and analysis, Frontiers in Public Health, 9 (2022) 816226.