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Artificial Intelligence in the Food Industry: Transforming Safety, Efficiency, and Sustainability From Farm to Fork

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ABSTRACT

Artificial intelligence (AI) is promptly changing the nature of food production and processing to increase safety, efficiency, quality assurance, and sustainability throughout the farm-to-fork chain. This review discusses the recent developments in AI in the food manufacturing industry, such as machine learning (ML), deep learning (Dl), computer vision (CV), hyperspectral imaging (HSI), robotics, Internet-of-Things (IoT) integration, and natural language processing. These technologies allow detecting contamination and fraud in real-time, near-perfect predictive maintenance less 30% unplanned downtime, automated quality checks with up to 96%–100% accuracy, AI-enabled predictive maintenance (PdM) has demonstrated its effectiveness by decreasing unplanned downtime in industrial case studies through a reduction rate that reaches 30% of total downtime, resource-efficient smart factories, and creative AI-driven formulation of products. New paradigms include digital twins, explainable AI, computational gastronomy, and cultured meat production, highlighting the transformative power of AI. Some of the solutions include standardized datasets, lightweight architectures, federated learning, and scalable deployment training programs. When used responsibly, AI can help create food systems that meet regulatory requirements while achieving sustainable development goals and circular economy standards, and all three Sustainable Development Goals, like Zero Hunger (SDG 2), Responsible Consumption and Production (SDG 12), and Climate Action (SDG 13).

Abbreviations: AI, Artificial Intelligence; API, Application Programming Interface; CAPEX, Capital Expenditure; CAGR, Compound Annual Growth Rate; CNN, Convolutional Neural Network; CNN-ViT, Convolutional Neural Network–Vision Transformer; CPU, Central Processing Unit; CV, Computer Vision; DL, Deep Learning; Edge AI, Artificial Intelligence implemented at the network edge; F&B, Food and Beverage; GFLOPS, Giga Floating-Point Operations Per Second; GPU, Graphics Processing Unit; HSI, Hyperspectral Imaging; I4.0, Industry 4.0; ICT, Information and Communication Technology; IIoT, Industrial Internet of Things; IoT, Internet of Things; ML, Machine Learning; MQTT, Message Queuing Telemetry Transport; OEE, Overall Equipment Effectiveness; OPC-UA, Open Platform Communications Unified Architecture; PLC, Programmable Logic Controller; ROI, Return on Investment; SCADA, Supervisory Control and Data Acquisition; SDGs, Sustainable Development Goals; SMEs, Small and Medium-Sized Enterprises; SERS, Surface-Enhanced Raman Spectroscopy; TCO, Total Cost of Ownership; XAI, Explainable Artificial Intelligence.

1 | Introduction

Artificial Intelligence (AI) refers to computer systems that can perform tasks requiring human intelligence, which has become part of the modern technological epoch, transforming industries on a fundamental level by introducing machine learning, which is the fundamental feature that allows the system to perform a complex set of tasks that should have been performed by human intelligence. Since adaptive education systems and complex problem solving are related to natural language understanding, AI has now become mainstream as it processes through large datasets at unheard-of speeds, thus making it productive, innovative, and evidence-based (Rashid and Kausik 2024). What used to be considered science fiction has become a reality in the healthcare, financial, manufacturing, and entertainment sectors within a short period. The food industry is one of the most promising sectors of AI transformation. Recent reports prove that AI has already been causing radical changes because of process optimisation, higher levels of safety and quality, and even innovative cooking (Jadhav et al. 2025). As the global food demand is predicted to increase 70% by 2050 to support almost 10 billion people, and food loss and waste currently contribute 8%–10% of anthropogenic greenhouse gas emissions, the need to adopt intelligent, resilient systems has never been more apparent (Falcon et al. 2022)

The applications of AI are now across the farm-to-fork spectrum, where these algorithms are used to optimise supply chains and improve operational precision, minimise logistical inefficiencies, and offer high-quality services at affordable prices (Helo and Hao 2022). Predictive tools include gastrointestinal theoretical models and partial least squares regression, in silico models and empirical models; but the most radical benefits are those brought about by computer vision, hyperspectral imaging, and ensemble learning in the areas of quality control, traceability, and safety assurance (Gbashi and Njobeh 2024). Remarkable performance is highlighted with the help of empirical evidence: the ensemble models of ExtraTrees and XGBoost can detect milk adulteration with a ninety-nine percent accuracy, compared to the one hundred percent accuracy of hyperspectral imaging to detect dairy contaminants(Revelou et al. 2025). The system of pork belly foreign object detection is a specialised hyperspectral Vision Transformer (ViT) based segmentation system that is highly robust to noise and spectral overlap in industrial applications (Ghimpeteanu et al. 2025). Likewise, a two-tier mobile platform with SVM and YOLOv3 gives 96.4% overall accuracy (98.5% classification, 85.7% defect localisation) to real-time banana grading (Zhu and Spachos 2021).

Looking from a market standpoint, the food and beverage artificial intelligence sector is growing very rapidly. In 2021, the worldwide market for food and beverage artificial intelligence was valued at USD 4.49 billion, and the predictions are showing astonishingly high growth at a CAGR of 45.4% with a target of USD 83.4 billion by 2029 (Nikolola-Alexieva et al. 2024). This growth is mainly due to the main goal of the industry to get the best quality products at very low prices, where AI plays a vital role through fast quality control, visualization of data in real-time, and uninterrupted analysis of operational trends, processes, and such. AI, mainly through these capabilities, helps the industry with spotting inefficiencies, suggesting measures to be taken, and improving the reliability of production, thus playing a dual role in meeting the market's demand for power and sustainability in modern food processing.

In addition to inspection, AI is a source of predictive maintenance, zero-waste approaches, sensory science, customised nutrition, demand forecasts, intelligent packaging, and shelf-life forecasts (Yang et al. 2025; Zatsu et al. 2024). According to bibliometric studies, the utilization of machine learning in food safety is growing exponentially and is closely linked with Industry 4.0 technologies, including AI, blockchain, and big data, which are currently inseparable from food science fields (Z. Liu et al. 2023). Another example of the potential to be creative is computational gastronomy, which uses machine learning and natural language processing to deconstruct recipes, make flavour predictions, and tailor diets (Goel and Bagler 2022). However, there are still significant impediments. In spite of these developments, scaling is limited by the traditional pillars of AI, which are data, algorithms, and computing power (Z. Liu et al. 2023). The undesirable data quality, heterogeneity, absence of standardisation, legacy system integration, high computing requirements, and ethical risks remain barriers to the trustworthy deployment (Agrawal et al. 2025; Yang et al. 2025). Training models using biased or incomplete data exposes them to errors with risks of supporting regulatory compliance and trust of stakeholders. The infrastructure lapses are disproportionately impacting the small and medium-sized enterprises (SMEs), and the lack of interpretability is undermining the trust of the operators in safety-critical situations.

More importantly, these systemic weaknesses cannot be overcome without causing the food sector to fulfill the full potential of AI. They need high-quality and standardised datasets, accessible and lightweight networks (including federated learning and efficient convolutional neural networks (CNN)), effective governance frameworks, and cooperative workgroups between manufacturers, regulators, and technologists (Das et al. 2025) Such actions will allow AI to go beyond individual and high-performance pilots and provide equitable, trustful, and planet-scale solutions that will improve food integrity, reduce environmental impact, and guarantee food security on the planet.

This review provides a critical discussion of artificial intelligence (AI) and machine learning applications in the fields of food production and processing, with references to food safety, fraud detection, traceability, and high-performance quality inspection through hyperspectral imaging and deep learning. It assesses predictive analytics in real-time risk and contamination prediction and equipment maintenance, and examines how AI could be used in reducing waste, the (circular) economy, and sensory-based personalised product development. The article identifies the problematic issues surrounding the data standardisation, computation requirements, and ethical governance, and suggests future research directions and best practices towards responsible and scalable implementation of AI in the global food systems.

2 | Methodology

2.1 | Review Design and Literature Scope

A methodical but integrative way has been taken to critically synthesize the latest developments in the utilization of artificial intelligence (AI) throughout the food industry, from farm to fork. The method used is based on a systematic literature analysis that meshes well with the thematic pillars that are given special attention in this paper: food safety, quality control, predictive maintenance, fraud detection, process optimization, sustainability, and the new AI paradigms such as digital twins, explainable AI (XAI), and computational gastronomy. The literature search focused on studies published between 2018 and 2025 and prioritized research from the years 2023 to 2026. The research employed a qualitative screening approach, which evaluated materials based on their relevance to the food system and their research methods, as well as the available performance metrics. The review establishes study selection procedures through transparent methods, which maintain consistency, although it does not apply PRISMA guidelines.

The research that served as a basis was discovered through a focused search using thematic terms that reflect the paper's scope and keywords: artificial intelligence, machine learning, deep learning, computer vision, hyperspectral imaging, predictive maintenance, food safety, quality control, food fraud, sustainability, smart manufacturing, digital twins, and circular economy. These terms were applied systematically to the main academic databases such as ScienceDirect, IEEE Xplore, SpringerLink, MDPI, Frontiers, and arXiv, paying particular attention to journals with a focus on food science, agricultural engineering, artificial intelligence, and sustainable systems. Only those studies that empirically validated or rigorously reviewed the application of AI technologies in actual or simulated food production conditions were selected. This eliminated the theoretical or purely speculative arguments that were not supported by methodological validation or performance metrics.

2.2 | Inclusion and Exclusion Criteria

The inclusion criteria given priority to the studies that (1) reported quantitative performance outcomes in terms of accuracy, recall, F1-scores, reduced downtime, energy savings, or waste minimization only; (2) mentioned the use of physical food processing infrastructure (for instance, vision systems on conveyor belts, IoT-enabled cold chains, and robotic packaging lines); (3) talked about difficulties that were very related to industrial scalability, like poor data quality, lack of model interpretability, legacy system incompatibility, or regulators' approval needed; (4) and finally, all these factors had a positive impact on at least one of the United Nations Sustainable Development Goals (SDGs), especially SDG 2 (Zero Hunger), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action).

The denial of the report to be included was also based on the restrictive criteria used, which were: non-food AI application areas (e.g., healthcare or finance) only, no empirical validation, outdated or non-representative datasets, or not framing the findings within food system constraints, i.e., hygiene, raw material variability, and batch processing dynamics.

2.3 | Thematic Synthesis and Analytical Approach

Thematic coding was used to map AI techniques to different functional areas of the food industry. For example, research using Vision Transformers (ViTs) and convolutional neural networks (CNNs) was classified under Quality Control and Inspection. On the other hand, research employing ensemble learning techniques (such as XGBoost and ExtraTrees) to identify contamination was included in Food Safety and Fraud Prevention. Similarly, studies utilizing multi-layer perceptrons (MLPs) or support vector regression (SVR) for energy prediction were categorized under Energy and Resource Management. The comprehensive comparison of AI techniques across studies was made possible by this structured classification. Model performance, data modalities (such as spectral, visual, and textual), and implementation limitations were all considered in the comparison. Reproducibility indicators, such as dataset size, hardware setup, training and validation processes, and deployment settings (e.g., pilot-scale *vs.* full-scale industrial contexts), received special attention. In order to capture the changing environment of AI in food systems, the evaluation also considers new research trends. Alongside well-known uses like vertical farming, cultured meat production, and generative AI for recipe formulation, recent research was analyzed, including early-access publications (such as arXiv submissions from 2024 to 2025). This approach provides a forward-looking perspective on the convergence of AI technologies and food science. The review tackled the ethical, regulatory, and socio-technical aspects as essential layers of analysis, which were in line with the authors' stress on "responsible AI." This comprehensive approach not only assesses the technological capabilities against the performance benchmarks but also considers the aspects of feasibility, equity, and sustainability.

3 | Global Context and Market Trends of AI in the Food Industry

The global food industry has been greatly transformed by technological advances, where Artificial Intelligence (AI) is one of the main triggers of future food production (Samad et al. 2025). Predictive maintenance, in-line processes, and real-time quality inspection will all be used to prospectively optimise production in AI-enabled smart food factories, which are efficient and environmentally friendly. The deployment of AI in supply chain management stands as a crucial trend because it decreases food waste while optimizing resource distribution and improving logistical operations, according to Samad et al. (2025).

The customization of food, along with laboratory-produced meat and plant-based products, is one of the most striking changes that have occurred in the food industry. The progressive transition to environmentally friendly and ethical food options, which summarizes the general trend, is mostly driven by consumer preferences (Kılkış et al. 2021; Samad et al. 2025). However, the major barriers to massive technological implementation are the steep implementation costs, data privacy issues, and disruptions to the workforce, which are mentioned as the negative effects of these developments. The authors argue that to reach market integration of AI-based food production systems, it will be necessary to address these issues by investing in them, by implementing regulations, and by ethically using AI (Özdoğan et al. 2021; Rejeb et al. 2022).

The food industry has received major breakthroughs through the development of personalized food products, which include lab-grown meat and plant-based alternatives. The shift shows how consumers increasingly prefer sustainable food choices that meet ethical standards (Kılkış et al. 2021; Samad et al. 2025). The market has not yet achieved widespread adoption because of three main challenges, which include expensive implementation costs, data privacy issues, and workforce interruptions. Successful market integration requires organizations to solve these problems with investments and regulatory frameworks and responsible AI deployment (Özdoğan et al. 2021; Rejeb et al. 2022).

4 | Evolution of Industrial Revolutions: From Mechanization to AI-Driven Food Systems

The development of industrial revolutions has significantly influenced food production and processing, which started with primitive mechanization and has progressed to more complex, AI-oriented paradigms, which accelerate efficiency, sustainable food production, and resiliency. This historical pattern does not only put into context the modern use of artificial intelligence in the food industry, but it also highlights the necessity of it, based on the global issue that the demand for food is expected to rise by 70% by 2050 to be able to feed a global population of nearly ten billion people (Falcon et al. 2022). Based on this, the following discussion outlines each revolution and its main features, technological breakthroughs, and food-specific implications, which highlight the smooth continuation of AI in the subsequent phases. The historical development of industrial revolutions and the corresponding transformation in food production systems, alongside the rapid expansion of the AI food market, are depicted in Figure 1.

4.1 | Industry 1.0: The Dawn of Mechanization (Late 18th Century)

The first industrial revolution, known as Industry 1.0, began in the late eighteenth century and was defined by the use of natural energy sources like wind and water as well as the mechanization of manual labor. A shift from agrarian to factory-based economies was made possible by the development of the steam engine, which revolutionized both manufacturing and transportation. Early mechanical milling and basic food preservation methods, such as canning, were adopted in the food industry during this time. With early adopters like Britain reporting increases of up to 200% through the use of steam-powered threshers and mills, these technologies greatly increased agricultural production (Bottomley 2025). Scalability and energy efficiency issues remained despite these achievements, underscoring inefficiencies that subsequent technical advancements, such as AI-driven optimization, aim to resolve.

4.2 | Industry 2.0: Electrification and Mass Production (Late 19th–Early 20th Century)

The introduction of assembly-line production, represented by Henry Ford's work, and the widespread use of electricity are what constitute Industry 2.0. Large-scale production,

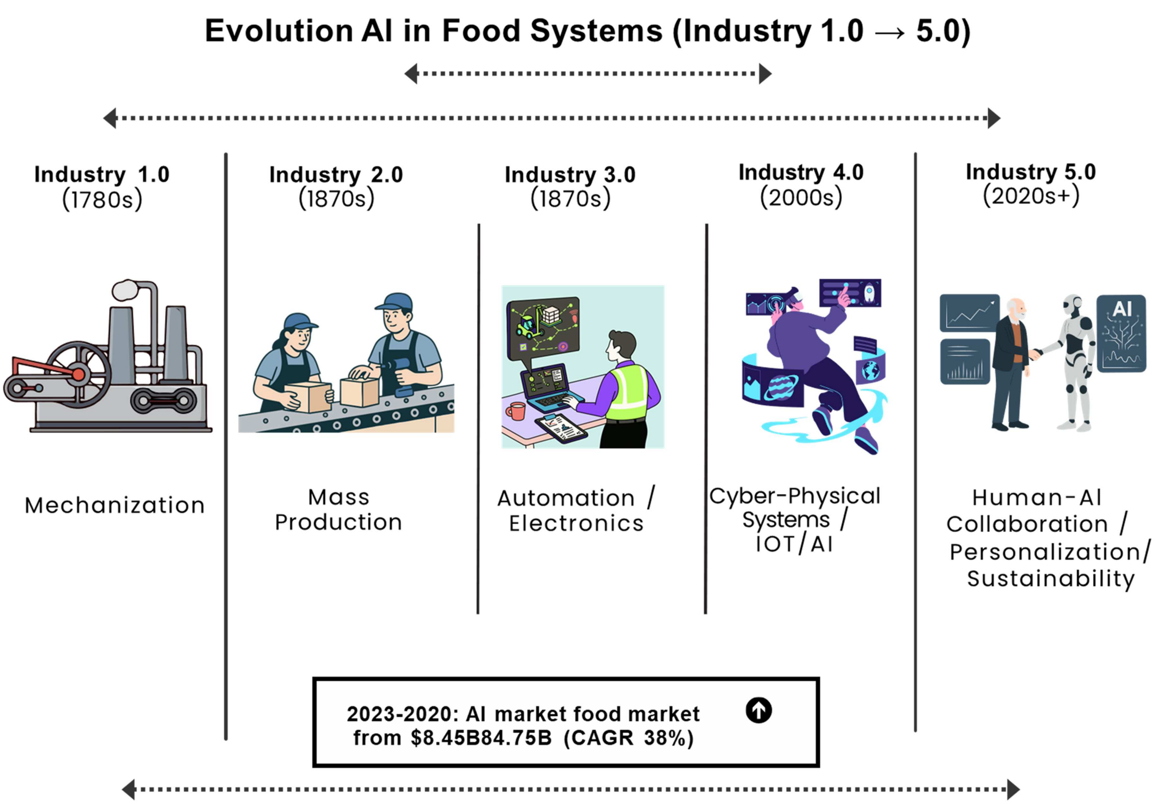

FIGURE 1 | Evolution of industrial revolutions in the food sector, illustrating the progression from mechanized factories (Industry 1.0–3.0) through digital integration and human-operated systems (Industry 4.0) to advanced human-AI collaboration (Industry 5.0), accompanied by projected growth of the AI food market from $8.45 billion in 2023 to $84.75 billion by 2030 at a CAGR of 38%.

standardization, and improved manufacturing efficiency were made possible during this phase. Electrification greatly decreased spoiling rates in the food sector, especially in meat processing, where reductions of 50%–70% were seen. It also made it easier to expand refrigerated systems and conveyor-based processing. The expansion of the U.S. meat-packing industry to over five million tons by 1920 is proof that this change encouraged the growth of large-scale exports (Lluch et al. 2025). Nevertheless, this model continued to rely significantly on manual labor, highlighting shortcomings that subsequent automation and AI-powered predictive systems seek to address.

4.3 | Industry 3.0: Automation and Digital Integration (Mid-20th Century Onward)

With the introduction of electronics, early computing systems, and programmable logic controllers (PLCs), Industry 3.0 made it possible to automate industrial processes and lessen the need for manual labor. A move toward data-driven manufacturing was signaled by the combination of numerical control (NC) and computer-aided design (CAD) technologies. This stage made it possible to implement sensor-based quality control systems and automate sorting in the food industry, which improved processing efficiency and lowered defect rates to less than 5% in some areas, such as contemporary dairy production (Falcon et al. 2022). However, these systems frequently functioned in isolated, compartmentalized contexts with little real-time adaptation; this shortcoming was later overcome by AI-enabled technologies like advanced analytics and hyperspectral imaging.

4.4 | Industry 3.5: Globalization and Offshoring (Late 20th Century)

The globalization of production and the shifting of industrial operations to areas with lower costs are the hallmarks of Industry 3.5, a transitional stage. This change greatly increased international trade and resulted in the creation of intricate global supply chains. The global food trade value increased from USD 300 billion in 1990 to USD 750 billion in 2010 as a result of the food industry's processing operations shifting more and more to areas like Asia and Latin America (Falcon et al. 2022). Extended supply chains, however, brought significant difficulties with regard to fraud detection, quality control, and traceability. The adoption of AI-enabled solutions, such as blockchain-based traceability systems and predictive analytics, has been prompted by these difficulties.

4.5 | Industry 4.0: Cyber-Physical Systems and Digital Connectivity (Early 21st Century)

Industry 4.0 creates intelligent, networked production environments by integrating cutting-edge technologies like cloud computing, cyber-physical systems, big data analytics, and the Internet of Things (IoT). Decentralized decision-making, real-time monitoring, and predictive maintenance are made possible by these technologies. Due in significant part to infrastructure limitations, adoption rates in the food industry are still very low (around 20%–40%) when compared to industries like automotive (45%–60%) and oil and gas ($> 80\%$). However, notable advantages have been documented, such as increases in production efficiency (51%) and cost savings (45%) among adopters. Furthermore, it has been demonstrated that IoT-enabled cold chain systems can cut food waste by as much as 14.8% (Kumar et al. 2024). AI technologies, such as computer vision for quality evaluation and machine learning for supply chain efficiency, support these developments.

4.6 | Industry 5.0: Human–AI Symbiosis and Sustainability Focus (Post-2020 Era)

Building on the digital underpinnings of Industry 4.0, Industry 5.0 places a strong emphasis on sustainability, human-centric design, and the fusion of AI with biological and cognitive systems. This paradigm emphasizes resilience, customization, and ethical production while encouraging cooperation between humans and intelligent robots. Early uses in the food industry include cultured meat production, adaptive agricultural systems, and AI-assisted precision agriculture. According to preliminary research, integrating robotics with AI-driven decision assistance can increase labor productivity and yield by 15% to 40% (Hassoun et al. 2024). According to projections, by 2030, almost 60% of food manufacturers would implement AI-driven sustainability strategies, which could reduce emissions by up to 20% through circular production models and efficient energy use (Majeed and Iftikhar 2026). When taken as a whole, these industrial shifts show an ongoing path of technical development that culminates in the incorporation of AI as a key facilitator of innovation in food systems. The food industry's AI market is expected to develop at a compound annual growth rate of 38%, from its 2023 valuation of USD 8.45 billion to USD 84.75 billion by 2030 (Majeed and Iftikhar 2026). AI is increasingly seen as a revolutionary agent in creating resilient, sustainable, and equitable food systems in addition to resolving historical inefficiencies.

5 | AI Technologies in Food Production and Processing

5.1 | Machine Learning and Deep Learning

AI's machine learning (ML) component uses data to identify trends and generate forecasts or judgments. Multi-layer neural networks are used in Deep Learning (DL), a subset of machine learning, to better evaluate complex data and find patterns. In contemporary food production and processing, ML and DL are essential enabling technologies. These methods improve analytical accuracy, enable data-driven decision-making, and assist automation throughout the supply chain (Khan et al. 2020). A class of algorithms known as machine learning (ML) finds patterns in data to carry out classification or prediction tasks. Multilayer neural networks are used by DL, a subset of ML, to analyze complicated and high-dimensional data, such as sensor outputs, spectrum signals, and pictures.

In food safety and quality control, traditional machine learning methods like Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting Regression Trees (GBRT) are frequently used. These models are frequently used for adulteration analysis, freshness evaluation, and contamination identification. For example, 99%–100% accuracy levels in identifying milk contamination and foreign items in meat products have been attained by combining hyperspectral imaging with ensemble learning techniques (Gbashi and Njobeh 2024). In a similar vein, Spachos (2021) achieved 96.4% accuracy in grading bananas by combining SVM with the YOLOv3 framework.

Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs), two deep learning architectures, have shown exceptional performance in automated visual inspection tasks. Textural anomalies, surface imperfections, and fine-grained flaws are all successfully detected by CNN-based algorithms. On the other hand, by capturing global contextual linkages and lowering sensitivity to background noise and object similarity, ViTs provide enhanced robustness in complex industrial situations (Ghimpeteanu et al. 2025). DL's capacity to carry out end-to-end learning, which does away with the requirement for manual feature extraction, is one of its main advantages.

ML and DL models are being used more and more for process optimization in addition to inspection jobs. These applications include automating production scheduling, optimizing storage conditions (such as temperature and humidity), and forecasting equipment faults. Computational gastronomy applications, like anticipating complementary flavor profiles and creating recipes with specific nutritional qualities, are made possible in product development by DL models combined with Natural Language Processing (NLP) (Dhal and Kar 2025; Yang et al. 2025). Furthermore, a promising method for real-time process control is reinforcement learning, which enables adaptive optimization of manufacturing processes to boost productivity and cut waste.

There are still a few restrictions in place notwithstanding these developments. The lack of model interpretability, high computing costs, and the scarcity of high-quality labeled datasets are the main obstacles. These limitations make regulatory approval procedures more difficult and impede model openness. Explainable artificial intelligence (XAI), transfer learning for limited datasets, and hybrid modeling techniques that combine ML, DL, and physics-based simulations have all been the focus of recent research to address these problems (Shadi et al. 2025).

The usage of XAI in food systems remains restricted because there exists a trade-off between understanding model decisions and achieving accurate predictions. The absence of standardized XAI evaluation frameworks hinders both regulatory acceptance and industrial deployment of contamination detection systems, which are used in safety-critical applications.

Table 1 demonstrates the synthesis of recent scientific findings on the applications, performance metrics, adoption challenges, and emerging trends of robotics in food manufacturing.

The models show high accuracy performance, but their results depend on experiments conducted in laboratories with specially selected small datasets. The method used to evaluate the system creates doubts about its ability to operate effectively in actual industrial settings, which experience constant changes in raw materials, environmental conditions, and sensor interference. The Support Vector Machine and Random Forest algorithms provide greater system understanding because they need less processing power, which makes them effective for use in minor projects. Deep learning models, which include Convolutional Neural Networks and Vision Transformers, exhibit better results when working with complex high-dimensional data, but they need extensive labeled data and substantial computing power. The selection of AI methods should depend on the specific context, which requires organizations to find a balance between precise results and system understanding and implementation with machine learning (Patil et al. 2026).

5.2 | Computer Vision

A crucial element of artificial intelligence applications in food processing and manufacturing is computer vision (CV). In order to carry out automated inspection, grading, and process control, it allows machines to collect, interpret, and analyze visual data via cameras and sensors. Through sophisticated picture capturing, pattern recognition, and deep learning algorithms, CV systems offer real-time, non-destructive, and extremely accurate quality assessment, greatly increasing operating efficiency (Dhal and Kar 2025).

Defect detection and quality grading are two of CV's main uses in the food business. Convolutional Neural Networks (CNNs) in conjunction with high-resolution imaging systems enable the detection of surface flaws, discoloration, irregularities in shape, and contamination in a variety of products, such as fruits, vegetables, meat, and baked goods. For instance, Zhu and Spachos (2021) achieved a 96.4% grading accuracy for bananas using a two-stage image-processing architecture that integrated Support Vector Machines (SVM) with YOLOv3. Similar to this, Ghimpeteanu et al. (2025) used a Vision Transformer (ViT)-based segmentation model integrated with hyperspectral imaging to demonstrate nearly perfect detection of foreign objects in pork belly under industrial conditions, successfully resolving issues with spectral noise and object–background similarity. Computer vision is essential for processing automation and monitoring, in addition to quality assessment. On production lines, AI-powered vision systems can quickly confirm fill levels, label accuracy, and packaging integrity. Additionally, its integration with robotic systems is being used more and more for automated packing and sorting, which lowers human error while increasing consistency and throughput (Houshmandi et al. 2026).

The actual performance of computer vision systems shows valuable potential for their use in practical situations. The majority of models use static datasets for training, which contain limited variations that do not match the changing conditions of industrial environments, which include occlusion, varying light conditions, and different types of products. The systems based on deep learning face a major challenge because they function as "black boxes," which makes it difficult to understand their operations and restrict their use in applications that require safety regulations. The development of hybrid systems, which combine spectroscopy and explainable artificial intelligence methods, shows promise for solving existing problems, but their

TABLE 1 | Presents a synthesis of recent scientific findings on the applications, performance metrics, adoption challenges, and emerging trends of robotics in food manufacturing.

Food manufacturing automation	Robotic automation significantly increases production output in food manufacturing.	Throughput increased by 31.2%in large-scale HMR production and12.0%in order-based production.	Baek et al. 2024
Robotic adoption across industries	Food manufacturing has the lowest robotic penetration compared to other industrial sectors.	Only 5% of industrial robots are used in food processing;25%in welding,33%in assembly.	Kim et al. 2025; Baek et al. 2024
Industry 4.0 integration	Robotics, alongside AI, IoT, and smart sensors, is transforming core food operations (preparation, processing, packaging, preservation).	Robotics is a central component of this transformation.	Hassoun et al. 2024; Wakchaure et al. 2023
Adoption barriers & benefits	Robotics improves consistency, quality, and sanitation, and reduces labor/waste, but adoption is hindered by high costs, the need for flexibility, and system customization.	Benefits confirmed; major constraints: cost, small-batch variability, ingredient diversity.	Sanfilippo 2024
Meal-kit packaging systems	In meal-kit packaging simulations, robot configuration critically affects performance.	Double delta robotachieved1.7×throughput versus single robot; single robot was slower than manual.	Kim et al. 2025
Precision food preparation	Robotics is expanding beyond heavy processing into precision tasks like beverage formulation using computer vision and closed-loop optimization.	Demonstrates trend toward precision robotics in product development (e.g., powdered beverages).	Szymańska and Hughes 2025
Human-robot collaboration (HRI)	Full automation is not always feasible; collaborative robots (cobots) enable flexible human-robot teamwork to meet variable production demands.	Cobots and HRI remain essential in food manufacturing/assembly.	Keshvarparast et al. 2024
Simulation for deployment planning	Simulation and modeling of robotic systems (layout, throughput, workforce utilization) are vital for informed investment decisions in food factories.	Simulation is an essential decision-making tool for robotics integration.	Baek et al. 2024
Research gaps & soft challenges	Technical advances outpace research on “soft” factors critical for scalability: consumer acceptance, taste/quality perception, food-safety-compliant maintenance, and cleaning.	Key gaps: hygiene compliance, user perception, and deployment economics.	Zhang et al. (2025)
Meat processing automation	Robotics enables breakthroughs in slaughtering, cutting, and deboning, improving safety, throughput, and reducing ergonomic risks for workers.	Addresses worker safety and efficiency in high-risk operations.	Lyu et al. (2025)
Future smart factories	Machine learning and vision-assisted robots are identified as pivotal for next-generation smart food factories and automated production lines.	ML/vision-integrated robots are a key enabler of future food automation.	Yang et al. (2025); Zhang et al. (2025)

ability to grow and their financial efficiency need more testing before companies can use them (Wilkinson et al. 2026).

The use of 3-D vision systems and multi-spectral imaging is further widening the range of CV to include more than RGB imaging. It is possible to estimate the volume, analyse the texture, and detect the contamination with high accuracy using hyperspectral imaging and a machine-learning model to classify spectral features (Sun et al. 2023). Additionally, CV systems can now be deployed on embedded platforms within a few seconds in real-time, and this was previously impossible due to the blistering development of edge-AI devices, allowing real-time analysis without cloud computing. Machine-vision systems on processing lines still face real-world constraints; scientists have already found the problems of occlusion, changes in lighting, and noise in the background (Qu et al. 2025) and have discussed the difficulty of capturing the dynamic motion of oysters on a conveyor belt as an example of a complex real-world system (Qu et al. 2025). Other researchers note that the difficulty in obtaining accurate automatic food recognition has been an outstanding area of research.

Investigations dedicated to small and medium enterprises (SMEs) demonstrated that technological challenges to the integration of vision and IoT with traceability systems are due to high costs, a lack of awareness, and data management and security issues. The latest studies emphasize the fact that deep learning and spectroscopic technology integration significantly enhance the quality of spectral data analysis (Lun et al. 2025a), which supports hybrid CV spectroscopy systems, transfer learning, and interpretable models as areas of promising research.

5.3 | Robotics and Automation

Robotization and automation of the food production and processing industries are occurring at an extremely high rate. Robotics and automation have already replaced the monotonous, dangerous, and precision-intensive work on the factory floor, including high-speed pick-and-place operations, portioning, tray loading, cooking, packing, and palletising.

The state-of-the-art system consists of a robotic manipulator and AI-based perception, such as vision, force sensing, and spectral input, and advanced motion planning, thus allowing the robot to handle a wide range of delicate and non-standard food items, including ready meals, fresh produce, and bakery products, with human-like dexterity and significantly enhanced uptime. In addition to these technical capabilities, the robot-centric cells increase throughput, minimise chances of contamination, lessen workplace injuries, improve the labour-shortage problem of the manufacturers, and increase flexibility in changing SKUs. More recent commercial implementations and experiments, including those of Chef Robotics and its flexible meal-assembling robots, show that AI-controllable robotics can be seamlessly integrated into an already existing production line with little footprint, with the number of ingredients under control changing dynamically through continuous learning to make adoption of AI-controlled robotics accelerate the process of adoption of technology by prepared meal and frozen food manufacturers. The adoption of robotics in meat processing, high-volume packaged goods, and meal assembly has been substantially developed at the sector level, reviewed, and meta-analyzed. However, studies are needed to solve the problems related to hygienic design of robots, high-speed vision in changing light, and safe human-robot cooperation on high-density production lines. The current development of edge computing, compliant gripper technology, generative motion planning, and camera-to-robot calibration is showing the possibility of new applications, like autonomous inspection robots, vision-guided portioning, and inline adaptive packaging; however, several challenges exist, such as high capital costs, food safety compliance, and complexity of integration(Lyu et al. 2025; Yang et al. 2025; Zhang et al. 2025).

5.4 | Internet of Things (IoT) and AI Integration

Internet of Things (IoT) devices and artificial intelligence analytics integration represent one of the key factors that drive the reactive to proactive, as well as prescriptive operations in the food processing and manufacturing industries. The AI models use continuous, high-resolution data streams produced by distributed sensors, such as temperature, humidity, vibration, gas, RFID/NFC, and edge computing units, as well as connected cameras in real-time quality control, predictive maintenance, cold-chain management, and automated traceability. Applicative research suggests that IoT-AI-based systems are capable of minimizing unexpected downtime and spoilage due to predictive maintenance and anomaly detection; resource efficiency can also be increased, and waste can be minimized throughout the supply chain through near real-time product provenance and response to recalls when blockchain is included (Dakhia et al. 2025). Many studies report that the technology stack, which consists of edge-to-cloud designs, digital twins, sensor fusion (vibration, acoustic, and thermal), and lightweight on-device models, has reached a stage of maturity that makes it deployable at scale to large-scale industrial applications. However, the key obstacles to adoption are data readiness, interoperability, cost, and cybersecurity, especially for small and medium enterprises and resource-constrained areas (Agrawal et al. 2025). In addition, regulatory use cases, like compliance monitoring and analytics based on the EU Deforestation Regulation and deforestation risk, where remote sensing, IoT, and AI integration are already being tested to validate sources and sustainability claims. Studies also reinforce regulatory use cases, e.g., compliance monitoring and EUDR/deforestation risk analytics, in which satellite, IoT, and AI technology are currently being tried to verify the authenticity of the origin and sustainability assertions. The literature advises that to scale impact, development of standardized data schema, hybrid edge/cloud analytics, modular implementation roadmap, and cross-sector partnerships should be sought to reduce capital barriers and develop workforce capability (Alimadani et al. 2025; Dakhia et al. 2025).

5.5 | Natural Language Processing (NLP) for Process Optimization

The implementation of Natural Language Processing (NLP) is opening up new frontiers of operational efficiency in terms of data-driven decision-making in food manufacturing and food processing. Existing NLP applications cover all steps of production, with authentication and filtering of compliance documentation and inspection reports being the first and the final steps, which are the analysis of unstructured feedback provided by customers, the texts of recipes, and the description of labels. In a recent survey by Discover Applied Sciences, the mechanisms by which the NLP systems can identify possible violations, maintain compliance assistance up-to-date, and identify possible risks to safety at an early stage, such as the sentiment-based analysis of business feedback, are described in detail. Therefore, such technologies can make corrective measures faster and increase food-safety monitoring (Dhal and Kar 2025).

At the same time, AI methods have been increasingly used in the food industry, especially transformer technology, as well as other large, pre-trained transformer-based models, which are used to categorise foods and predict quality scores based on nutritional information (or simply based on the food labels). A large study performed on large food-label datasets showed that a combination of transformer-based representation and

XGBoost outperforms traditional bag-of-words methods with unprecedented accuracy (98%, on average, when classifying large food categories and 0.87R2, on average, when predicting nutrients) (Hu et al. 2023). Moreover, recipes with higher quality coherence and creativity are produced by LLaVA-Chef, a model that uses multimodal large language models fine-tuned on recipe generation. Moreover, KERL (2025) and hybrid systems are used to combine food-specific knowledge graphs with large language models to provide personalized recommendations of recipes with nutritional information (Mohbat and Zaki 2024; Senath et al. 2024). The interconnected applications enabled by IoT integration within AI-driven food manufacturing ecosystems are illustrated in Figure 2.

6 | Applications of AI in Food Production and Processing

6.1 | Quality Control and Inspection

Hyperspectral imaging (HSI), which uses artificial intelligence and deep learning, is transforming the process of food quality control as it allows non-destructive quality control that is fast and exceptionally precise. As an illustration, Yang et al. (2025) found that a combination of HSI and convolutional neural networks (CNNs) generated a highly dependable determination of the internal and external quality of fruits and vegetables, and greatly exceeded conventional manual methods in their precision and speed of detection. Furthermore, Ahmed et al. (2025) addressed the extensive industrial application of the HSI and non-destructive imaging technology and noted its efficiency in real-time monitoring during the main production line processing steps, such as sorting, grading, and contamination detection. A further study by Lun et al. 2025b) found that deep learning is an augmented spectroscopic and imaging technology, including HSI, which provides a cost-effective and scalable method to spectral-quality inspections in a variety of food-processing environments. All of this evidence shows AI-based imaging technologies now provide equal performance to traditional quality-control methods while maintaining their ability to enhance existing industrial processes. Nevertheless, these technologies require industrial adoption to depend on three specific elements: their operational expenses, accessibility of required data, and ability to maintain performance during different processing conditions.

6.2 | Predictive Maintenance and Process Optimization

Artificial intelligence (AI) and automation in the food-processing industry have enhanced the optimisation and efficiency of processes through modern technology. Predictive maintenance (PdM) is a type of AI-driven application that is a balance between conducting minimum downtime and maximum operational performance. Through machine-learning algorithms and sensors, like vibration, acoustic, and current-signal analysis, PdM systems can detect mechanical

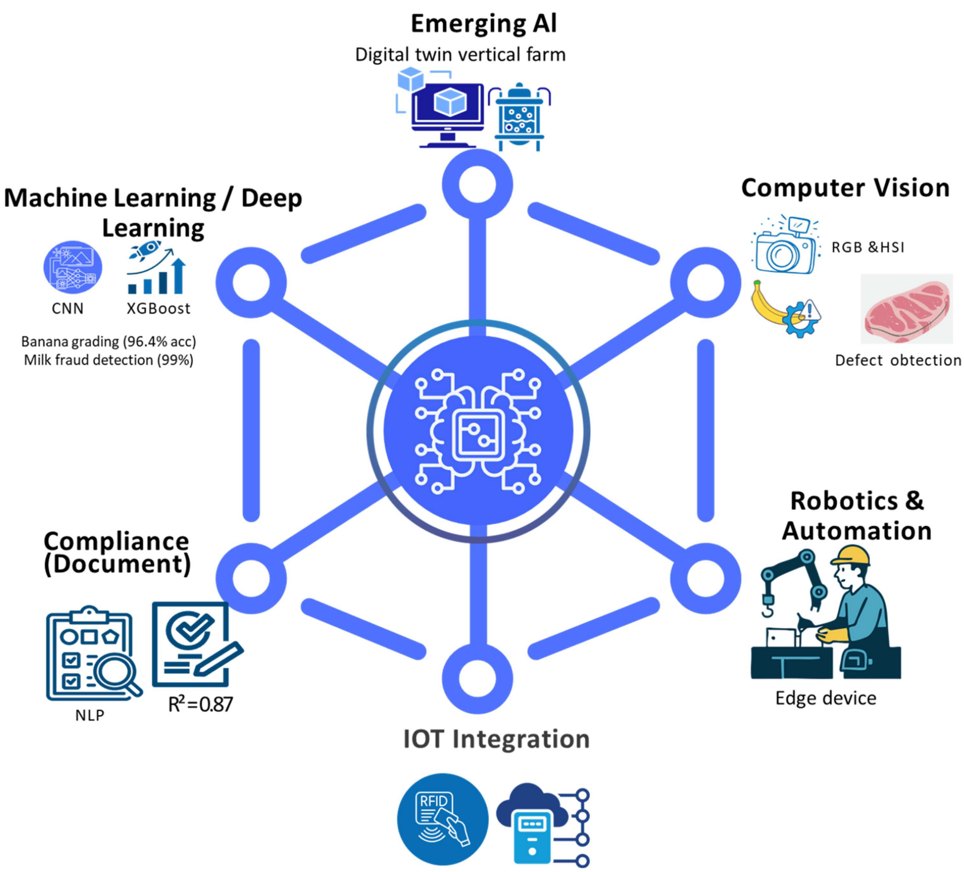

FIGURE 2 | Central role of Internet of Things (IoT) integration in AI-powered food manufacturing systems, connecting key applications such as data analytics, quality inspection, predictive maintenance, robotics, traceability, contamination detection, and real-time monitoring.

irregularities prior to critically damaging conditions happening, allowing maintenance personnel to respond on a conditional basis instead of doing reactive maintenance. Moreover, the case study by Fernández-Peláez et al. (2024) shows that PdM is effective on a monoblock filling line, where a machine-learning-based process can predict short-term production halts with an acceptable precision that enables timely corrective measures to mitigate unplanned downtime significantly. Data-driven maintenance plans can reduce failure rates, increase equipment life, and reduce the use of spare parts in manufacturing industries (Dalzochio et al. 2020; Psarommatis et al. 2023). Empirical evidence in the food industry indicates that predictive maintenance programme adoption leads to considerable operational enhancement, e.g., a 10% higher overall production uptime due to decreased emergency maintenance and improved scheduling. In addition, PdM helps prevent energy consumption and waste of materials, which happens due to the failure of equipment and, in this regard, is consistent with the goals of smart, resource-efficient manufacturing promoted under the Industry 4.0 and 5.0. Overall, these learnings imply that predictive maintenance is a critical part of AI-based procedures. Fault detection is a key use of artificial intelligence in food-processing equipment, in the form of predictive maintenance (PdM). It uses sensors that are responsive to different parameters, such as vibration, acoustic, thermal/IR, electrical, and pressure/flow, with machine-learning and deep-learning models, including random forests, support vector machines, and CNN/LSTM/transformer hybrids, to predict failures, predict remaining useful life (RUL), and perform non-disruptive interventions based on hygiene-critical processes. Recent investigations place AI into the food supply chain, associating PdM with less downtime and more consistent thermal profiles, as well as less excessive processing and waste using online condition monitoring and soft-sensor modelling in SCADA/PLC systems. These results also present a wide picture of the integration of PdM pipelines, including the IoT-enabled telemetry and feature learning with probabilistic health indices and explainability to meet the regulatory traceability and validation criteria. Emerging trends in this field are AI-based digital twins to maintain the scenario, respond to product changes, and highly model under the conditions of limited or noisy sensors commonly found in wetclean processes, which are needed to maintain throughput and food safety. Taken together, these studies depict how reactive/preventive maintenance has been transformed into a data-driven, risk-based maintenance, thus enhancing uptime, energy savings, and consistency of products in the modern food factories (Agrawal et al. 2025; Z. Liu et al. 2023; Zhang et al. 2025).

6.3 | Food Safety and Contamination Detection

The integration of machine learning in hyperspectral imaging (HSI) and various imaging methods has had a significant impact on the identification of food safety hazards: microbial contamination and contamination by chemical adulterants, including chemicals, among other risks. Soni et al. (2024) reveal that HSIs, with the help of advanced chemometric and machine learning models, can detect bacterial, viral, and fungal contaminants in various food matrices with high accuracy, thus making it effective in real-time to monitor food and preventive control with the help of early detection in food safety. Synthesizing the works of various authors in the area of mycotoxin detection, Kabir et al. (2025) offer a brief overview of the HSI-based machine learning methods to detect and quantify mycotoxins in cereal grains and nuts, including the difficulties of applying the algorithms as benchmarks of algorithmic performance variability and the need to scale the methods accordingly. Furthermore, further research has found the implementation of even more comprehensive artificial-intelligence-based approaches to mycotoxin contamination detection, which again validates the necessity to combine spectral imaging with predictive modelling as a way to reduce hazards before they occur (Aggarwal et al. 2024). To detect physical contaminants, the hyperspectral imaging (HSI) combined with deep-learning algorithms, including convolutional neural network long short-term memory (CNNLSTM) models, has already attained the potential to recognize minute embedded dangers, namely bone fragments and nutshell fragments, with an accuracy of up to 99% in controlled experiments (Xie and Zhou 2023). In addition to identifying hazards, Nie et al. (2024) show that with a deep-learning-enhanced HSI system, it is not only possible to identify the presence of fungi but also to identify both the geographical origin and the type of grain, including millet, which can be used to consider both issues of safety and authenticity. These papers show a frantic pace of development where multispectral/HSI systems, along with machine learning, are improving the sensitivity, throughput, and interpretability of the detection of a large variety of substances. The current models face their most challenging obstacle because they fail to duplicate their results in multiple food types and various environmental situations. The model performance experiences major impacts from three factors, which include contamination levels, sample composition, and spectral signatures. The absence of standardized datasets and benchmarking protocols restricts researchers from conducting cross-study comparisons and implementing their work at large-scale operations. Future research should develop strong scientific models that transfer across multiple fields while creating shared datasets to support research that requires reproducible results and industrial use (Balakrishnan et al. 2025).

6.4 | Product Development and Formulation

The swift introduction of artificial intelligence (AI) and machine learning (ML) into food development and formulation has spawned the development of more efficient innovations that are consumer-focused. Al-Sarayreh et al. (2023) reported that the use of inverse design and deep generative networks is changing food formulation, whereby the interactions among ingredients, sensory properties, and product quality are maximized. AI models allow researchers to practically develop new formulations, so there is a significant reduction in the application of expensive, time-intensive laboratory tests.

On the same note, Azeem et al. (2025), showed that the use of AI in formulation tools, including generative modeling, digital twins, and natural-language processing (NLP), could lead to a reduction in the number of physical prototyping by 90% at best and a faster reformulation process that took months to be fastened by several weeks, and a net cut in R&D expenditures by

30%–60%. All of these developments enable real-time testing of scenarios, predictive flavour modelling and sustainable ingredient replacement, which are necessary to create new food products that would meet nutritional, environmental and regulatory specifications.

In addition to such technological advances, Witkowski and Wodecki (2025) found AI to be an essential element during the new-product development (NPD) and product-management phases, especially in the first phases of idea generation, market forecasting, and consumer-insight extraction. On the contrary, they observed that the use of AI is mostly limited to the later phases, such as concept testing and post-launch assessment, due to the disaggregated data systems and company obstacles. The authors underscore the idea that organisations aiming to gain the most out of AI must first build strong data backbones, develop interdepartmental collaboration, and see AI as an ongoing intelligence layer in product development and management. These transformations to a large extent mark the shift of the time when data will be the most significant impetus, which in its turn will make food innovativeness flexible and scalable. With the integration of human expertise and computational/algorithmic intelligence, food manufacturers can hasten their research and development, attain high performance of their products, and easily adapt to changes in consumer preferences and environmental sustainability issues.

6.5 | Energy and Resource Management

Artificial intelligence (AI) is increasingly becoming an essential asset in energy and resource management that can be applied to the food production and processing industry, and the main goal of its use is to improve operational efficiency, sustainability, and cost efficiency. In another study, the authors of E-Electronics note that demand forecasting with the help of AI, supported by the Industrial Internet of Things (IIoT), industrial cyber-physical systems, and digital twins will make energy consumption in the production industry virtually identical to scheduled consumption, which will allow to eliminate about 7% of energy consumption and emissions in pilot projects (Rojek et al. 2024).

In contrast, the multi-model of multi-layer perception (MLP) and support vector regression (SVR) with data on energy consumption at the factory level has proved to predict power usage patterns at a high degree of accuracy and hence enhance resource planning (Lee et al. 2023). Within this particular context of food processing, machine-learning models like k-Nearest Neighbours (kNN) and random-forest regression were found to assist with optimizing heating profiles, leading to decreased process time and less energy use without affecting the quality of the product, and increasing it in some instances (Đaković et al. 2024).

Research into process heat in the food industry has highlighted the energy-intensive nature of the industry, which contributes to around 0%–11.6% of the industrial energy needs of Europe, and has also shown a large potential to achieve AI-driven process-heat recovery and optimised control as a way of achieving higher efficiency. These studies demonstrate how AI is taking the food processing industry to a new stage in energy management by minimizing peak demands, guiding electricity procurement choices, enhancing the utilization of thermal systems, and supporting sustainability goals with the help of AI methodologies in predictive modelling, digital-twin infrastructure, regression, and control optimization. The primary AI applications in food manufacturing systems and their associated quantitative benefits are summarized in Figure 3.

7 | Current Status and Technological Advancements

7.1 | Industry Adoption and Case Studies

Some recent evidence suggests that artificial intelligence application in food production is no longer just an experimental activity; instead, the major focus now lies on quality control with the use of vision and hyperspectral cameras, predictive maintenance with the help of the Internet of Things and machine learning (ML), traceability with blockchain and analytics, and product development with machine learning and natural language processing to ideate and predict sensory, the strategy today is one of placement of technology across various departments.

The maturity of the technology and its application in operational contexts have been documented. Ellahi et al. (2023a) show that blockchain traceability and IoT-related sensor networks are already in place and are integrated with analytics platforms to make quick recall and improve provenance verification. AI applications also list industrial applications of computer vision as 100% inline inspection, machine-learning models to estimate the remaining useful life of equipment, and digital-twin models to plan maintenance and optimise energy. The given reasons to the assertions that quantifiable advantages can be realized, including less unplanned downtime, faster defect detection, better traceability, and faster response to recalls, in case AI is implemented into the available SCADA/PLCs and enterprise data stacks with an investment in data curation, edge computing, and validation processes (Agrawal et al. 2025; Ellahi et al. 2023b; Jayan et al. 2025). However, the literature also displays common obstacles identified in the multi-site case studies: the integration of legacy systems, lack of skills by the workforce, the normalising of data, and regulatory justification remain the barriers to both SMEs and the process of extending pilot projects to lasting production programmes (Agrawal et al. 2025).

Ellahi et al. (2023b) and Jayan et al. (2025) provide a sensible, outcomes-based adoption curve in which companies align AI initiatives with operational key performance indicators, including downtime, defect rate, shelf-life accuracy, and time-to-market, and, in this manner, maximize their investment returns and deliver research-based case studies on which wider industry implementations are informed.

7.2 | Integration of Smart Factories

The implementation of artificial intelligence into the Industry 4.0 models has made the processing of food in factories more

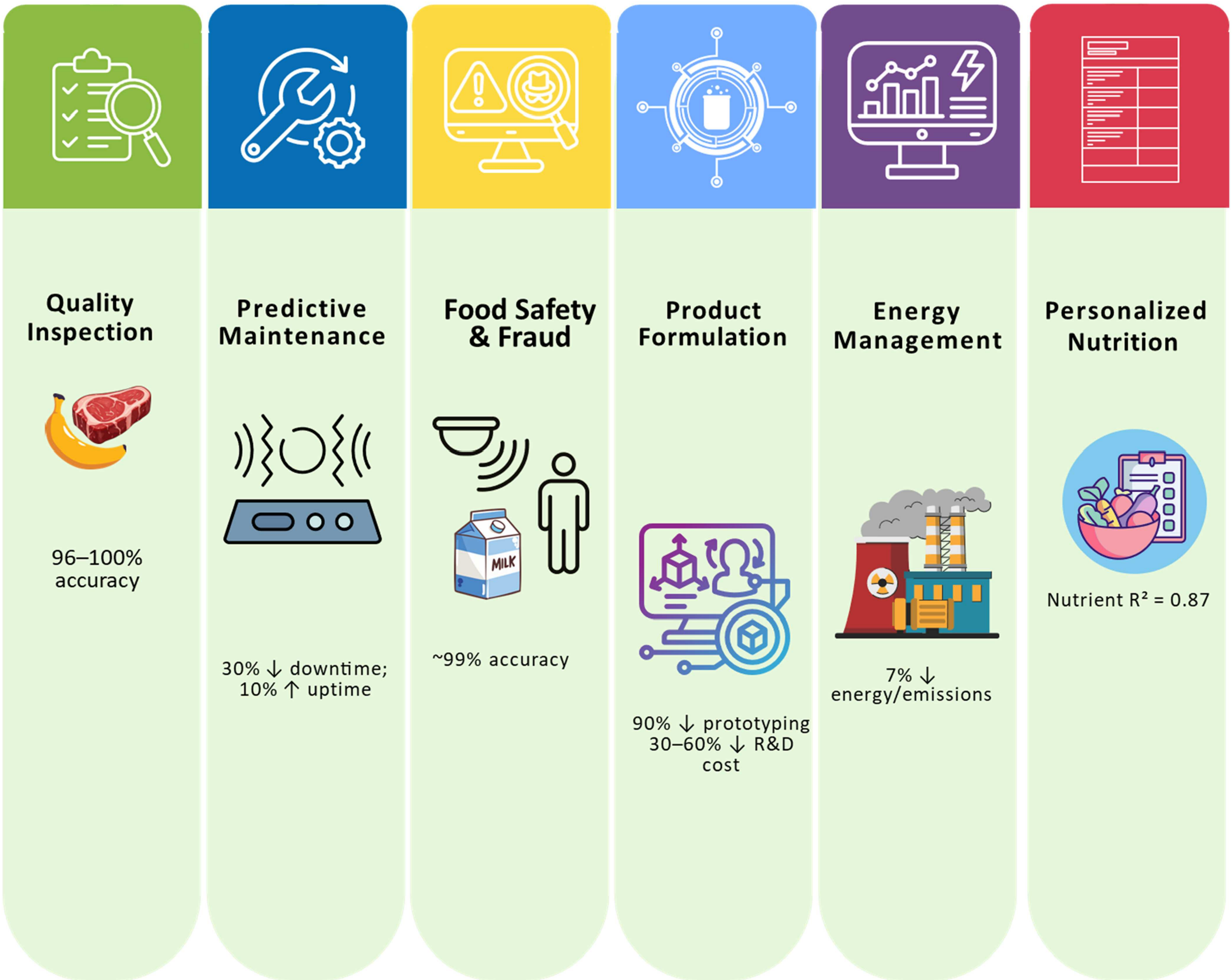

FIGURE 3 | Key applications of artificial intelligence in food manufacturing, demonstrating performance metrics in quality inspection (96%–100% accuracy), predictive maintenance (30% reduction in downtime; 10% increase in uptime), food safety and fraud detection (~99% accuracy), product formulation (90% reduction in prototyping and 30%–60% in R&D costs), energy management (7% reduction in energy/emissions), and personalized nutrition (nutrient prediction $R^2 = 0.87$).

efficient and fast, turning them into intelligent factories with cyber-physical, digital twins, IoT sensors, robotics, and real-time analytics. Agrawal et al. (2025) state that convergence of AI, IoT, big data, and blockchain not only streamlines the supply-chain operations but also improves product traceability and eventually makes operations within food-supply chains more sustainable on the environmental, social, and economic levels. Moreover, a number of studies clarify the use of digital twins in the food processing industry, where the virtual models of physical systems are used to optimize resource use by simulating performance and contributing to quality and sustainability decision-making (Abdurrahman and Ferrari 2025). On the other end, AI-based inventions in industrial research on smart manufacturing have made AI a point of entry in terms of productivity enhancement, right next to labor and machine investments across Industry 4.0 ecosystems (Lindberg 2025). However, there are still ongoing issues related to the compatibility of old systems, data availability, human resource readiness, and implementation of reliable AI, especially in small to medium-sized operations (Windmann et al. 2024). Together, these sources provide a picture of the potential and the reality of implementing AI-based capabilities at the very heart of the modern food production setup.

7.3 | Advancements in AI Algorithms for Food Processing

Dhal and Kar (2025) outlined how AI algorithm is being developed specifically to serve the needs of food processing, thereby increasing the accuracy, productivity, and flexibility, and how AI methods, such as deep learning, computer vision, multifaceted machine learning, natural language processing, and reinforcement learning are changing the industry in terms of safety, quality, and operational processes throughout the lines of processing to supply chains. Therefore, the enhancement of the algorithms affecting the food industry is supplemented by real-world improvements. According to Agrawal et al. (2025) and Misra et al. (2020), machine learning and big data are integrated into the production process of ingredient mixing, energy use, and other parameters through supervised and robotic cloud-based models, which offer optimization. Particle Swarm Optimization (PSO), which is an evolutionary algorithm, is already in use in the agrifood sector to optimize logistics, energy usage, and resource allocation, as discussed by Arévalo-Royo et al. (2025). A study conducted by Amore and Philip (2023) explores the importance of AI in engineering enzymes and precision fermentation and details how machine learning accelerates enzyme design and microbial strain editing, which are two key variables that facilitate the innovation of large-scale food processing.

Arora et al. (2025) performed predictions of levels of food processing, according to the NOVA scale, through nutrient profiles. By creating highly accurate ($F1 > 0.93$) and high-performing ML models, including LGBM, Random Forest, Gradient Boosting, and NLP models, they offered effective tools for categorization and processing assessment according to nutrients. Besides, physics-inspired machine learning (PIML) models are becoming the new paradigm to model microscale plant-based food drying, combining neural networks with physical models to improve accuracy and predictability in the simulations, as described by Batuwatta-Gamage et al. (2025). These algorithmic developments have given the food industry a fully developed AI toolbox; deep learning, evolutionary optimization, and physics-based hybrid models have each established a presence among the AI tools in the food sector. As a result of this, it is now possible to construct intelligent, agile, and scalable processing systems, which are able to cover the entire gamut, both in ingredient accuracy and drying kinetics.

7.4 | Data Analytics and Big Data in Food Production

According to recent studies, data analytics and big data play a central role in the revolution of the food industry, as they allow a company to make choices that are superior, more efficient, and less risky. The implementation of AI and big data in the food industry promises a new age of productivity, excellent quality control, consumer-level insight, and the development of Industry 4.0 technologies like smart sensors, robots, and digital twins (Ding et al. 2023). Additionally, Plakantara and Karakitsiou (2025) reported the importance of AI, blockchain, IoT, and big data as the foundation of proactive and data-driven risk management systems that will enable the detection of safety risks, improvements in traceability, and the creation of dynamically resilient supply chains. Moreover, a thorough examination by Agrawal et al. (2025) illustrates that real-time analytics, which include the integration of the IoT, robotics, and AI, are transforming resource optimisation, cutting down waste, and maintaining the quality of food products during manufacturing processes. However, there are also issues like high implementation costs and a deficiency in governance. Lastly, Siddique et al. (2025) mention the convergence of cloud computing, mobile sensors, IoT, and blockchain, which increases the opportunities to monitor and track food, as well as allowing conducting more rapid and agile maintenance adjustments and decisions throughout the supply chain.

Although current studies show rapid progress, their main limitation stems from missing standardized assessment methods and testing of real-world systems. The proprietary nature of datasets used in AI model development and testing restricts researchers from reproducing results and comparing different models. The existing diversity in preprocessing methods, together with feature extraction techniques and performance measurement standards, creates obstacles for establishing universal testing benchmarks. The solution to these challenges needs collaborative work on creating open-access datasets together with establishing uniform testing methods and conducting assessments in real-world industrial settings (Hao et al. 2025).

8 | Key Challenges in AI Adoption for Food Systems

8.1 | Technical Limitations

Numerous significant problems persist to this day in the technical constraints of the use of artificial intelligence in food production. Among such limitations, it highly hinders the effective and large-scale deployment on the industry level:

8.1.1 | *Computational Demands and Data-Related Barriers*

AI systems are often associated with large amounts of computational power, as well as a high-speed internet connection and efficient cloud or edge infrastructure. In the case of food manufacturing, especially when remote or low-resource type is involved, this infrastructure is oftentimes lacking, which complicates the implementation of the solutions and limits the viability of real-time analytics (Agrawal et al. 2025). In manufacturing processes, sensor-derived data are usually presented in noisy, incomplete form and exist in various forms such as time-series, image, and text logs. Lack of standard data schema and common ontological structures also negatively affects data integration and schema development, as well as cross-system interoperability (Bačiulienė et al. 2023; Dakhia et al. 2025).

8.1.2 | *Integration Challenges With Legacy Systems and Lack of Model Interpretability*

Many food-processing plants still use the old industrial control systems (ICS), including Supervisory Control and Data Acquisition (SCADA) based systems and Programmable Logic Controllers (PLCs), which were not originally intended to support data-driven analytics but to be deterministic controllers. Therefore, the adoption of artificial intelligence and machine learning (AI/ML) solutions in the manufacturing process faces a number of substantial challenges. First of all, the older control equipment and their corresponding communication protocols (Modbus, Profibus, OPC Classics, etc.) often do not have a standardised high throughput application programming interface, forcing practitioners to either use protocol gateways, historians, or model-specific middleware to extract and normalise telemetry to train a model and make inferences (Ding et al. 2023; Folgado et al. 2024). Moreover, the need to have low-latency control loops in real-time is also incompatible with the compute and data-transfer requirements of big AI models. This conflict makes it necessary to use edge-compute partitioning, soft sensors, or digital-twin architectures to keep inference on theoretical knowledge locally, which is the need to retain control determinism, while still providing insight to models (Folgado et al. 2024; Ucar et al. 2024). Moreover, the data available on the shop floor are usually heterogeneous, small in size, and are not labelled, such as crude SCADA logging times, event signals, and image feeds. As a result, it takes a significant amount of time to extract-transform-load (ETL), synchronize data, and annotation to create strong models to be deployed to production (Ding et al. 2023; Leite et al. 2025).

Besides, the connection of legacy IC systems to analytics pipelines raises cybersecurity and safety risks. Segmentation, secure gateways, and anomaly detection mechanisms should therefore be included in the integration process to avoid the enlargement of the attack surface as well as protect the integrity of the process (Folgado et al. 2024; Ucar et al. 2024). Technical problems will automatically lead to financial and operating overhead. The expenses of hardware and software purchasing, capital and operating expenses, are compounded by the necessity of protocol converters, historians, edge servers, and validation workflows, which require multidisciplinary personnel during installation and regulatory acceptance. The cumulative effect is more likely to slacken the implementation, particularly in the case of small and medium-sized enterprises (Ding et al. 2023; Ucar et al. 2024). In general, the above cautious, sluggish approaches, architecturally mindful (edge computing, historians, API layers), and permissive to the creation of cross-functional expertise, are the ones that ultimately allow AI to be integrated in food processing to eliminate these obstacles and realise safety, reliability, and large-scale implementation. Lastly, sophisticated deep neural network AI systems are often viewed as black boxes. Their transparency and justification of their decisions destroy operator trust and reduce uptake, particularly in safety-critical systems like food control systems.

8.1.3 | *Model Degradation and Maintenance Over Time*

Models of artificial intelligence (AI) used in food-processing settings will experience slow performance degradation over the years because of the fluctuating conditions of operation, sensor wear, modification of raw material characteristics, and control strategy modifications. All these are referred to as concept drift and model degradation. Any change in the concepts underlying data may be safety-critical since the statistical patterns that a model trained may have learned during training may not be the same in production, leading to unforeseen mispredictions unless detection and mitigation strategies exist (Hinder et al. 2024). Predictive maintenance and condition monitoring systems require model recalibration to be a common requirement. This can be credited to the fact that every production line has certain unique characteristics, including different loads, wear, and environmental conditions that make the initial models assume different conditions than the actual ones within the operational conditions of the line. According to the authors, under these conditions, it is necessary to use online monitoring, incremental learning, domain-adapting methods, and a lightweight edge retraining pipeline in order to keep the inference accuracy at a respectable level (Garcia et al. 2025). New drift-detecting and diagnosing frameworks have been suggested based on recent engineering studies, which integrate novelty/novel-event detectors, ensemble learners, and continuous-learning loops to find the causes of drift and engage in retraining or sensor recalibration to reduce unexpected failures and avoid incorrect retraining cycles (Chapelin et al. 2025). All these studies support the idea that model maintenance on the production phase is an ongoing and expensive process that entails the following steps: (a) continuous monitoring of drift; (b) performing rapid but limited retraining or incremental update (preferably at the edge); (c) developing workflows to obtain and verify data to provide regulatory traceability; and (d) implementing human checks to verify that model updates do not undermine safety-related decision-making (Chapelin et al. 2025; Garcia et al. 2025; Hinder et al. 2024).

8.1.4 | *Security and Trustworthiness Concerns*

The growing interdependence of AI analytics, IoT sensors, and industrial control systems in the food processing industry creates new attack points that attackers can use to break the integrity of the models or disrupt production. Backdoor insertions: Covertly manipulating machine-learning model behaviour without being immediately detected by standard validation protocols, data-poisoning attacks, where training data sets are intentionally contaminated, present a threat to the integrity of machine-learning-based monitoring and decision systems (Sangwan et al. 2023). The adversarial (evasion) examples phenomenon during inference can be used to misclassify impure or unsafe products by visual-recognition models or outlier-detection models, resulting in false negatives or false positives, which may directly compromise food safety. Furthermore, sensor impersonation and method-level attacks can still penetrate the telemetries serving the analytics pipeline, thus facilitating the performance of unsafe control actions (Nankya et al. 2023; Salmi and Bogucka 2024).

Besides the integrity attacks, model-extraction and membership-inference threats also mean that confidential information like formulations or supply-chain databases may be leaked, which weakens confidentiality and reduces trust in the business. According to the literature, these risks in the context of food production can also be reduced in a multi-layered way: very strict network segmentation and hardening of industrial control systems according to the ISA/IEC 62443 best practices; checking the provenance and cryptographic integrity of training data; detecting anomalies or adversarial-robust training in the pipeline; monitoring model drift and query behavior; and human-in-the-loop validation of safety-critical decisions (Nankya et al. 2023; Sangwan et al. 2023).

Such measures are necessary to ensure operational availability and product safety, as well as to retain trust among stakeholders, since AI systems take on more processing roles in the food industry.

8.1.5 | *Scalability and Adaptability Limitations*

Scaling AI systems to multiple product lines and flexible food processing facilities is the biggest impediment to mass implementation. Models trained using a small number of SKUs or with data based on the sensors of one plant usually do not work well when used in other products, packaging types, or environments. This imbalance can be attributed to the shifts in domains, the variability of sensors, and the varying distributions of the features that are specific to production. As a result, numerous deployments must either customise their locations inexpensively or undergo a complex transfer-learning pipeline instead of a simple rule of thumb train once, and you can deploy everywhere (Ding et al. 2023; Ghag et al. 2024). Additionally, the multiplicity of food matrices, including differences in moisture, texture, and surface reflectance, with recipes or suppliers always changing, requires the re-validation and retraining of models continuously, which increases the cost of operations and slows the extraction of value by manufacturers (Bačiulienė et al. 2023).

The real constraints, such as a lack of labeled information about new SKUs, differences in camera or sensor apparatus, and variance in conveyor velocity or lighting, further hinder the introduction of solutions to different locations without engaging in advance changes, which adds to the additional workload needed to prepare sites from a specific viewpoint (Ding et al. 2023; Ghag et al. 2024). The food sector is forced to face regulatory validation, auditability standards, and the need to show unified performance of different production locations, which all create administrative and engineering overheads that hinder horizontal scaling of AI solutions in the industry (Agrawal et al. 2025). The approaches to addressing these challenges are the need to have standard datasets and benchmarks, modular AI systems that facilitate transfer learning and domain adaptation, and industrial best practices in site validation and large-scale data curation.

8.2 | Data Quality and Availability

The main concerns of AI implementation in food production systems relate to the quality, fullness, and availability of data resources. The efficacy of AI depends heavily on the quality of the input information; therefore, the most frequent problems involve overfitting, unrepresentative data, implicit bias, and lack of alignment between the training data and real-life working conditions, which have a devastating effect on the model's robustness and generalizability. Moreover, data silos and incompatibility of formats are also a hindrance to data integration. These different sources, sensor logs, laboratory tests, and textual inspection records are to be aligned, and sometimes it is crucial to pre-process the data to avoid misinterpretation or analytics delays (Dimitrakopoulou and Garre 2025).

The wide variety of food types and laboratory needs makes the entire process of creating high-quality, labelled data not only expensive but also time-intensive, making it one of the greatest barriers to scaling AI solutions to new products or processing lines (Wang 2025). In addition, large datasets in food systems express inefficiencies in data collection, incomplete coverage, and data islands, especially in particular testing workflows where manual sampling or irregular standards lead to the absence of data that cannot be obtained in some situations(Ding et al. 2024). These factors promote model bias, increase the chances of misclassification, and reduce reliability, particularly in systems that are meant to control contamination or assure product safety.

8.3 | Regulatory and Ethical Issues

Food production and processing systems utilizing AI have not only technical concerns but also very complicated regulatory and ethical concerns. The most prominent and controversial problem is the problem of algorithmic bias and unfair results: models trained on non-representative data may be systematically discriminating against any of the producers, members of the supply chain, or consumer groups unless it is accompanied by data governance and fairness checks in the development lifecycles(Craigon et al. 2023; Manning et al. 2022). Moreover, augmented use of personal and business information in AI processes, including gathering, combination, and subsequent use, causes issues of legal and confidentiality, which in turn entails the need to employ explicit provenance, consent management systems, and robust privacy-sustaining actions to earn business confidence and legal professionalism (Z. Liu et al. 2023). Additionally, the broad regulatory framework (e.g., the EU AI Act and sector-specific regulations) places new liabilities on the high-risk AI systems, which means that manufacturers should embrace risk management, post-market oversight, transparency, and human control. This not only increases the complexity and cost of compliance but also impacts the small and medium enterprises disproportionately (Aboy et al. 2024). Moreover, ethical issues also include environmental and social aspects, including the energy footprint of massive models, fair distribution of AI advantages, and the possible displacement of skilled labor, which may require lifecycle impact analysis and policies that will foster distributive benefits as opposed to concentrating the benefits among a small group of participants (Agrawal et al. 2025; Manning et al. 2022). Lastly, some studies in the industry suggest governance strategies that combine responsible-innovation practices, warm-up/reflexivity/inclusion/responsiveness, regulatory sandboxes, or sectoral guidance to do real-world compliance experiments and multi-stakeholder data-trust models to balance innovation and responsibility and the common good (Aboy et al. 2024; Craigon et al. 2023). Together, these results suggest that AI requires ethical protection, common standards, and measures that are commensurate in order to be used in food systems in a transparent and socially acceptable way.

The existing regulatory frameworks, which include the EU AI Act, lack practical implementation methods for food systems because there are no specialized guidelines and validation methods for that field. The ethical issues that involve data privacy, algorithmic bias, and transparency requirements need both technical solutions and governance systems to establish responsible AI implementation throughout the supply chain.

8.4 | Cost and Infrastructure Barriers

The expenses and infrastructure were major challenges that slowed down the entire food production industry from embracing and harnessing AI technology as a positive force in many ways. The SMEs were especially affected negatively, so that they had to carry the burden of heavy investment in capital and the necessity to use more expensive technologies.

8.4.1 | *High Costs and Infrastructure Limitations*

Initial and continued costs of AI systems, IoT sensors, robots, and their infrastructure are costly beyond reasonable imagination and make them not affordable to the vast majority of organizations, especially small ones. These expenses include hardware, software, training, and maintenance; doubt about the payoff remains a factor in reducing the willingness to invest unless there is an attractive business case (Dhal and Kar 2025). The necessary infrastructure to support AI systems in real-time production settings (e.g., the low-latency network, the high-speed internet connection, and the cloud or edge computing) is not widely available to many food producers. This means that SMEs that lack this infrastructure face challenges when it comes to the deployment and scaling of AI (Agrawal et al. 2025).

8.4.2 | Integration With Legacy Systems

Many food-processing companies will have to upgrade their industrial control systems, including PLCs, SCADA, and other industrial control systems, which have been in operation for a long time, to enable them to support AI and IIoT features. This requirement has propelled the modernization cost in both the first phase and in the context of recurrent spending. The research behind this assertion comes about due to the existence of legacy devices and monolithic SCADA architectures, which do not conform to modern data platforms. Reports on Industry-4.0 reviews and automated tests have continuously shown that older PLC/SCADA designs often use vendor-specific or proprietary fieldbuses or OPC Classic interfaces, thus requiring protocol translation (OPC UA gateways or protocol converters) or message-oriented middleware (MQTT brokers, Sparkplug), which requires additional CAPEX, integration engineering, validation, and cybersecurity investment. Also, industrial control system/SCADA security evaluation and food-system synthesis have indicated the necessity of industrial data historians, network partitions, and edge calculations to maintain control-loop determinism alongside providing low-latency inference. All these contribute to the overall cost of ownership and increase the project schedules. As a result of this, the lack of standardization and Industry-4.0-preparedness, including networking, historians, and the use of OPC UA, has been repeatedly found to impede scalable and cost-effective AI applications in food production, unless firms use architectures in stages and adopt common integration standards. Due to these factors, the author recommends initiating dialogue on the topic and adopting sustainable solutions. Based on these reasons, the author suggests starting a conversation on the matter and implementing sustainable solutions (Ding et al. 2024; Folgado et al. 2024; Kovič et al. 2024; Nankya et al. 2023; Orjuela-Garzon et al. 2024).

8.4.3 | Skill and Workforce Gaps

Skilled labour has been cited as a major impediment to industrial artificial intelligence integration in the food processing industry. Organizations are finding it challenging to hire emerging employees with the necessary combination of domain (food/process) and data/AI skills. Besides, the process of training current operators and engineers is a lengthy and expensive task, thus slowing down the deployment rate and raising the overall program cost (Kovič et al. 2024; Zahoor et al. 2025).

Recent food informatics studies have highlighted the fact that the professional competencies of the existing workforce and the lack of ready technical personnel form the key obstacles in the process of switching AI pilot projects to full-scale production systems. This is a challenge mostly to small and medium-sized enterprises (SMEs), which usually have no budget to conduct training or no specialised AI talent (Agrawal et al. 2025; Orjuela-Garzon et al. 2024). In turn, these human-capital gaps and the need to fill them require collaboration between industry and academia and investment in organized reskilling programs so that AI deployment in the food sector would be sustainable and cost-efficient in the long run.

The financial limitations and absence of technical knowledge, together with the unpredictable nature of investment returns, create greater difficulties for SMEs. The current situation shows that most SMEs operate only at their pilot projects because they require affordable AI solutions and supporting policies to make wider use of the technology possible.

8.4.4 | Uncertain Return on Investment (ROI) and Cost Justification

The problem of the uncertain payback (ROI) continues to pose a major challenge to the massive adoption of artificial intelligence in the food sector. Uncertainty, significant initial investment in different sensors, cloud or edge computing, and systems interconnection, along with recurring investments (data management, retraining models, and regulatory verification), also lean towards the short-term financial benefits, hence leading manufacturers to a wait-and-see approach to AI (Ding et al. 2023; Orjuela-Garzon et al. 2024). The incorporation of AI with the current production systems, including old PLC and SCADA architecture, increases the technical complexity and reveals the latent costs of operation, which negatively influences the economic viability of the implementation. Moreover, small and medium enterprises are disproportionately impacted by the cost of workforce reskilling, compliance, and model validation, making the ROI ambiguous and a pilot project to a fully functioning AI system transition slow (Agrawal et al. 2025; Orjuela-Garzon et al. 2024).

8.5 | Workforce Training and Transition

The attention has been focused on significant challenges and new methods of worker training and transition caused by the implementation of AI and Industry 4.0 in food processing and manufacturing. The case of (Zahoor et al. 2025) clearly shows that AI and automation are the key factors driving workforce transformation, which requires strategic investment in employee competency and high-performance work systems (HPWS). The mediating variable between the adoption of technology and employee engagement, flexibility, and sustainability of productivity is training, specifically AI literacy and data analytics. According to manufacturing case studies, there is a growing tendency to replace humans with machines in performing tasks that need a low level of skills, particularly in automating the repetitive processing of food products like cracking eggs and shelling them. At the same time, the demand for high-skilled positions (AI system operators, maintenance technicians, and data analysts) is increasing, which, at the same time, makes the workforce upskilling a critical defining factor of organizational performance (H. Liu et al. 2024). According to the global labor market analyses, manufacturers are worried about AI-induced changes in skills and are addressing the issue by retraining most of their employees, about 71%. However, as has been noted, the unskilled workers are the most influenced by such skills changes and hence have the greatest training gaps. Such a situation can be changed only by proactive policies aimed at combating the problem; otherwise, it will further increase inequality (OECD Employment Outlook 2023).

Virtual Reality (VR), Generative AI, and Digital Twins have been discussed as the foundation of future training and learning technologies in recent years, with high levels of scalability and personalization. Recent studies reported that immersive VR training might shorten the duration of skills acquisition in the manufacturing industry and, at the same time, demonstrate the main difficulties of such technology application, such as high cost and inaccessibility. Similarly, a Generative AI tutor, which uses low-fidelity digital twins and AI-based sentiment analysis to customize training and improve trainee engagement, has demonstrated an accuracy of more than 80% and a decrease in training time in experimental conditions (Ipsita et al. 2025; Lin et al. 2025). According to the existing academic literature, the main keystone to effective AI implementation in the food industry lies in the thorough training of the workforce: traditional education, learning with technologies (e.g., VR and AI instructors), and targeted training tracks according to the new job descriptions. The primary challenges hindering widespread AI adoption in food manufacturing, particularly for SMEs, are outlined in Figure 4.

9 | Future Perspectives

9.1 | Emerging AI Technologies

Artificial intelligence technologies are coming up to realise mass systemic improvement of food processing and production, and thus adding intelligent, sustainable, and personalised systems. The state-of-the-art AI-sensory technologies, including advanced electronic noses and tongues, are being engaged to improve the non-destructive quality measures and flavour profiling. Further, non-destructive quality evaluation and flavour profiling are supplemented by smart packaging, however, with embedded sensors and blockchain, to track storage conditions continuously and take proactive action to prevent the risk of spoilage. It helps to prolong the shelf life of goods and enhance food safety (Zatsu et al. 2024). Digital twins are AI-based and are used to offer an active digital replica of processing environments, making it possible to simulate production processes, energy optimisation, and predict contamination. The technology allows testing different scenarios within a short timeframe without interrupting the actual manufacturing lines (Dhal and Kar 2025; Vilas-Boas et al. 2023; Yang et al. 2025).

Explainable AI algorithms like SHAP and Grad-CAM have now started to find applications in food engineering in response to the increasing need for trust and compliance in the industry. These techniques enable operators by exposing the ghost bands or parts of an image on which a model bases its choices when conducting quality checkpoints, and improve the visibility of the whole process to the regulators (Arrighi et al. 2025). Cultured meat is also an area where AI is increasingly being used, including the selection of cell lines, the development of culture media, and image-based measurements, which are all refined to speed up the development process and make the production of lab-grown meat resource-efficient (Todhunter et al. 2024). The use of AI technologies in vertical farms allows achieving high yields, resource efficiency, and sustainability due to optimised light, climate control, and crop surveillance with the assistance of machine learning, IoT, and robotics.

Computational gastronomy is a multidisciplinary field of artificial intelligence and food science that generates data-driven knowledge on how recipes can be optimized, flavour-paired, or customized nutrition. Through the use of various culinary databases, molecular flavour databases, and machine learning it develops models capable of recreating both recipes and sensory experiences, thus allowing the creation of food products that meet specific needs. According to Bagler and Goel (2024), computational gastronomy is an approach according to which

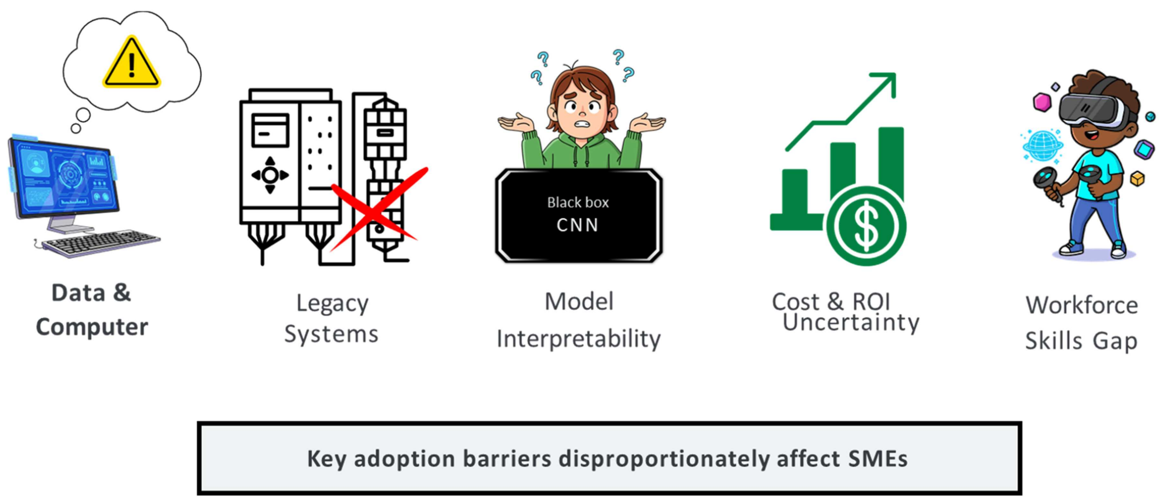

FIGURE 4 | Major barriers to AI adoption in the food industry, including issues with data and computing resources, incompatibility with legacy systems, lack of model interpretability (black-box CNNs), cost and ROI uncertainty, and workforce skills gaps, which disproportionately impact small and medium-sized enterprises (SMEs).

flavour, nutrition, and sustainability can be mathematically combined, and AI-supported creativity in recipe creation can be offered. These advances are heavily backed by foundational resources like FlavorDB, the flavour-molecule database (Garg et al. 2018), and RecipeDB, which is the connection between ingredients, nutrients, and cuisine metadata (Batra et al. 2020). The recent progress in the field has also introduced the application of chemoinformatic descriptors for the prediction of sensory properties and the guidance of food pairing. Meanwhile, machine-learning algorithms classify recipes based on nutritional preferences to facilitate personalised meal suggestions (Yamaguchi et al. 2024). Together, these tools can form a strong basis of AI-assisted personalisation and nutritionaln such spheres as recipe creation, nutrition optimization, and sustainable food production.

9.2 | Sustainability and Environmental Impact

The growing power of artificial intelligence (AI) in the sphere of sustainable food production, resource optimization, and circular economy practices can be observed. Artificial intelligence (AI) solutions that unify the Internet of Things (IoT), robotics, computer vision, and predictive analytics allow food producers to waste less, use resources better, and achieve fluctuating product quality due to real-time monitoring and adopting changing decisions (Agrawal et al. 2025). In food production, AI applications combine sustainable management of the resources with better yield forecasting, climate-responsive irrigation, and a more efficient process of produce through the supply chain (Onyeaka et al. 2023). The digital twins technology also plays a vital part in the sustainability agenda as it allows changes in designs and optimisation of product lifecycles, which, accordingly, leads to minimised material wastage and minimised emissions along with an increase in the efficiency of operations (Sajadieh and Noh 2025; Seegrün et al. 2023).

9.3 | Global Collaboration and Policy Development

International cooperation in AI policy concerning food and agrifood systems has shifted from general statements presented at the highest level to particular governing instruments emphasizing multi-scalable stewardship, trust building, and capacity development. The importance of inclusive, place-based, and territory-seafood arrangements, as well as the presence of powerful policy instruments, is highlighted in food-systems governance analyses, which can be utilized to handle the trade-offs between productivity, equity, and the environment (Janin et al. 2023). Studies aimed at advancing AI in the agricultural field not only underscore how accessibility, clarity, and responsibility of data are the main criteria to build trust among stakeholders, but also observe that policy-research collaborations and institutional arrangements will be needed to put reliable AI into practice by farmers and supply-chain participants (Alexander et al. 2024). The AI-powered agriculture roadmaps propose spaces to trial, i.e., regulatory sandboxes, standards of interoperable data, and training to the smallholders and local institutions, so that they can engage in the digital transitions equitably (Pandey and Mishra 2024). Besides these sector research, international surveillance and examinations of food systems acknowledge governance and resiliency as crucial places of focus in coordinating international action, thus emphasizing the necessity to quantify shared pointers, and multi-stakeholder unions to drive policy congruency (Schneider et al. 2025).

9.4 | Integration With Circular Economy Principles

Artificial Intelligence might support the implementation of the circular economy in the food production and processing industry by minimising waste, promoting resource usage, and helping the use of by-products by making data-driven decisions. As an example, models in demand-forecasting and inventory-optimisation can minimise losses caused by overproduction and expiration; sensors to monitor the quality of products, together with predictive spoilage models, allow the redirection of items at risk to redistribution or up-cycling; machine-learning-based routing and redistribution platforms can match surplus with demand to keep using the food instead of going to landfills (Onyeaka et al. 2023). AI also helps close material loops by determining the pathways of processing by-products, which can be reused - like the calculation of the amounts of extraction or composting streams that can be obtained, and the optimization of energy, water, and input utilization at the process level, hence minimizing the operational environmental impact throughout the life cycle. These measures have been shown to enhance efficiency in materials and reduce emissions both in industrial case studies and modelling exercises (Oladapo et al. 2024). Finally, AI, combined with policy and governance systems, including data standards, transparency tools, and circularity indicators, do not only support but also demonstrate how widely the idea of the circular economy is in practice at the regional and national level by country-level analyses that connect AI applications to the goals of the circular economy and identify the institutions that facilitate the latter (Pathan et al. 2023).

9.5 | Alignment With Sustainable Development Goals (SDGs)

The series of recent studies proves the variety of ways in which AI technologies can enhance the United Nations Sustainable Development Goals (SDGs) regarding food systems, agriculture, environmental protection, infrastructure, and how the country collaborates globally: The analysis of the use of AI-aided agriculture to serve small-scale farmers in Nigeria showed that the implementation of AI technologies, such as automated weeding, pest surveillance, animal monitoring, and the ability to access the market online, directly boost the production level, minimise the use of intermediaries, and improve the quality of living, which will further the SDG 2 aims (Amuda and Alabdulrahman 2024).

Some of the SDGs currently being achieved through the use of AI tools in food systems are those related to productivity, health, infrastructure, innovation, responsible consumption, climate resiliency, and global cooperation. Precision agriculture, which applies AI to data gathered using sensors, drones, and satellites, not only enhances yield but also optimises inputs (water and fertilizers) and, thus, is beneficial to SDG 2 (Zero Hunger) and SDG 12 (Responsible Consumption) due to the minimised losses and the use of resources more efficiently (Marvin et al. 2022; Omotayo et al. 2025; Sharma et al. 2022). The connection to SDG12 is intensified by forecasting demand, optimising stocks, and predicting spoilage over sensors throughout the supply chain, and reduces the greenhouse-gas emission caused by the disposal of unused food (Ding et al. 2023; Manzoor et al. 2024). The tools that directly support SDG 13 (Climate Action) are climate-related risk analysis and adaptive decision-making support, facilitated by digital twins, satellite-based yield and climate models, and system-wide simulations, which offer information on the most resilient agricultural and supply-chain measures (Hariyani et al. 2025; Marvin et al. 2022; Nahar 2024). Analyses with a wider spectrum and alignment of AI with the SDG agenda have found pathways; they have discovered that AI can accelerate the objectives of SDG3, SDG9, and SDG17 (health, industry/innovation and partnerships) under the conditions that there are governance, equity, and access measures in place so that the disparities are not reinforced (Maghsoudi et al. 2025; Nahar 2024; Vinuesa et al. 2020). The role of AI in supporting circular economy practices across the food production and consumption cycle is visualized in Figure 5.

10 | Conclusion

The application of artificial intelligence (AI) in the food industry is transforming the industry by ensuring the process is faster, safer, and more innovative at every phase of production and consumption. The different spheres of the field in which AI

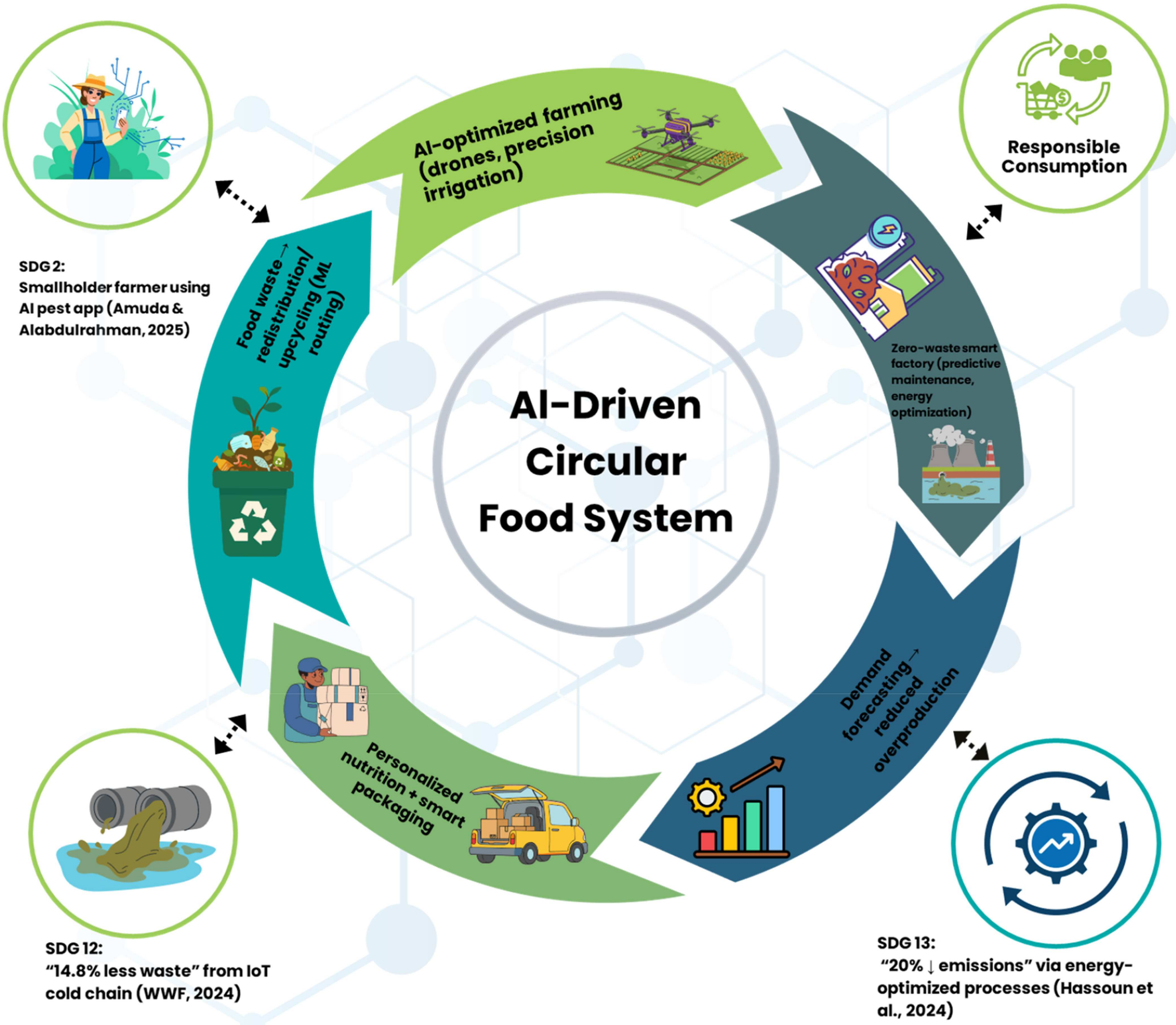

FIGURE 5 | Integration of artificial intelligence in promoting circular economy principles within the food value chain, encompassing AI-optimized precision farming, zero-waste smart factories, demand forecasting to reduce overproduction, personalized nutrition and smart packaging, food waste reduction through upcycling and routing, and responsible consumption.

is used, including quality control, predictive maintenance, energy control, and environmentally friendly formulation, all indicate the possibility of addressing long-term inefficiencies and, at the same time, addressing the needs and goals of the global community, including food security, environmental safety, and climate resilience. The capabilities of such technologies as deep learning, computer vision, robotics, and IoT-enabled systems are no longer limited to pilot projects only; they are also shifting towards mass adoption by industrial applications in smart factories and precision agriculture. Such changes become more consistent with the Sustainable Development Goals (SDGs), which help to fight hunger, minimize waste, and adapt to the outcomes of climate change. To maximize the advantages of AI, it is not just about the radical potential but also about the removal of the barriers that currently prevent it, including poor data quality, technological limitations, regulatory challenges, expensive implementation, and the need to train staff. These challenges cannot be overcome without interdisciplinary research, including not only computer science but also food engineering, agricultural sciences, and social sciences, to come up with scalable and ethically responsible solutions. Furthermore, the international collaboration of industry players, governmental regulators, and scholars will provide the basis on which harmonisation of regulations, ease of access to data, and the spread of AI-based advances will be equitable. Summing up, AI is believed to be the main tool of future food systems; its effectiveness will be defined through the adequate incorporation of technological advancement with the three components: inclusiveness, ethicality, and sustainability. In case this happens, AI will not only be a considerable help to the modernisation and efficiency of the food industry but also a key collaborator in creating resilient, safe, and sustainable future food systems.

Author Contributions

Muhammad Waqar: conceptualization, methodology, software, data curation, formal analysis, visualization, writing – original draft, project administration. **Mariyam Shahid:** conceptualization, methodology, data curation, formal analysis, writing – original draft. **Manat Chaijan:** supervision, writing – review and editing, validation, resources. **Worawan Panpipat:** resources, supervision, validation, writing – review and editing. **Djilali Benabdelmoumen:** conceptualization, investigation, supervision, writing – review and editing. **Ahmed Mediani:** conceptualization, supervision, writing – review and editing, validation, investigation. **Abdifetah Ibrahim Omar:** writing – review and editing, supervision. **Sabrin R. M. Ibrahim:** writing – review and editing, supervision. **Qudrat Ullah:** conceptualization, validation, visualization. **Temesgen Anjulo Ageru:** supervision, investigation, data curation, conceptualization, writing – review and editing.

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Ethics Statement

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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