Journal of Applied Artificial Intelligence
https://jaai.sabapub.com
ISSN: 2709-5908

2026 Volume 7, Issue 1: 1–35
DOI: https://doi.org/10.48185/jaai.v7i1.2044

Next-Generation Artificial Intelligence for Sustainable and Intelligent Food Production Systems: A Review

Luma Alharbawee[1*], Baydaa Sulaiman Bahnam[2], Suhair Abd Dawwod[3], Nicolas Pugeault[4]
[1,2]Department of Artificial Intelligence, College of Computer Science and Mathematics, University of Mosul, Mosul, 41002, Iraq
[3]Department of Management Information Systems, College of Administration and Economics, University of Mosul, Mosul, 41002, Iraq
[4]School of Computing Science, University of Glasgow, Glasgow, G12 8RZ, UK

Received: 02.03.2026 • Accepted: 28.05.2026 • Published: 04.06.2026 • Final Version: 30.06.2026

Abstract: AI has become an irreplaceable power in altering the perception of the population about all branches towards sustainability, making climate friendliness a sustainability aspect, and smart food production is one of the biggest losers of the change. In a world where environmental difficulties are building up and the pressure to sustain the global food supply keeps rising, artificial intelligence exhibits feature particularly useful to enhance the level of production, waste minimization and enhancement of quality at every phase of an agricultural or food value chain. The article is a systematic review of recent advances in artificial intelligence that can be used in food systems, such as optimization of resources and reduction of waste at the supply chain level; predictive food production by livestock management and precision agriculture; and high sensitivity food production processes. The review demonstrates that the combined capabilities of the modern technologies to include robotics, computer vision, deep learning (DL), machine learning (ML), and the Internet of Things (IoT) advance smart and sustainable manufacturing systems. On the one hand, a great number of quantitative data indicate that artificial intelligence is capable of accomplishing monitoring of current crops, in-sourcing diseases and pests in crops, intelligent control of irrigation and food safety standards. Nevertheless, challenges remain to be huge and disallow mass implementation of such technologies: infrastructure issues, inefficacies in handling information such as the one produced by IoT devices, budgetary factors related to additional investment and the ethical considerations that come with implementing algorithms in such sensitive systems.

Keywords: Sustainability, Smart Production, Food Processing, Artificial Intelligence, Machine Learning.

1. Introduction

The food system of the world is facing a combination of previously unseen and interconnected problems including the unprecedented explosion of food demand and the catastrophic effects of climate change. Natural resources are being used in an unsustainable way. This mandates the need of long-term solutions to food security - novel and sustainable solutions [1,2]. The introduction of the Artificial Intelligence (AI) as the groundbreaking technology that can simplify the food supply chain segments between the production and distribution and consumption stages are a necessary tool of dealing with these complexities [3,4].

---

[*] Corresponding Author: luma.akram@uomosul.edu.iq

The unsustainable global food system that is revealed again in the COVID-19 pandemic emphasizes the urgency of structural adaptation and automation to provide food to a projected world population of ten billion in 30 years in a sustainable manner [5,6]. At the same time, climate change puts pressure on these strains that drain valuable resources such as land and water extreme weather patterns and shifts in planting seasons shatter the backbone of the agricultural production [7]. It is imperative to realize that the global population will only increase by more than 70 percent before 2050 whether one likes it or not with the advanced means of technology such as artificial intelligence. The use of artificial intelligence, such as machine learning, big data analysis, robotics and the Internet of Things (IoT) are solutions to increase productivity beyond output sustainability in measures of economic and environmental protection resource efficiency all along the agri-food value chain is of utmost importance [8, 9,10,11,12].

The rapid development of AI, it penetrates the usual sphere now it is closely connected with the food category, which is directly connected with human health and environment conservation [13]. This integration represent change in thought. Moreover, in information, all of a sudden, one can monitor and project manage the entire food system [14]. Recent advances in deep learning, neural networks, natural language processing and image recognition can now create intelligent production systems that can read a great deal of agricultural and food data instantly. It is the same in the case of animal breeding. The practical application is like using AI based computer vision technology to automatically sort and grade food based on appearance, detect pollutants and check product quality. This enhances food safety and factory productivity besides lowering the cost of managing human operator labor and preventing errors in the work of human operators [15,16,17,18].

Machine learning and deep learning are now common AI methods that can be applied to the food industry and aid in such areas as yield prediction, waste prevention, quality management, and optimal supply chain optimization [19,20,21,22,23]. The artificial intelligence is not limited to productivity. It also assumes the larger task of sustainability, such as promoting environmental friendliness, resource conservation and refining grain handing efficiency [24,25]. AI offer predictive analysis where consumers are changing their habits depending on the volatility of historical data and in this manner, also serves to reduce food waste on fluctuating levels of demand. It is now most related to changes in inventory that anticipatory relate to future consumption expectation. And it may have an even greater task in future, by influencing those adjustments to most effectively minimize waste [26,27]. Salient models such as ADAPTS indicate the direction of strategic implementation of machine learning in sustainable agricultural systems based on the source of data and objectives [28,29]. Recent investigations have depicted that AI offers combined scientific structures to help in a transition between reactive administration procedures and predictive self-regulating systems of industry 5.0 [30]. Even the most basic food processing systems have AI to develop hyper efficient automated production systems that dynamically learn sensor and computer vision data to provide intelligent quality management, predictive maintenance to reduce downtime and operational continuity [31,32,33].

The use of AI and logistics data is one of the key transformations towards building agile, flexible, and resilient supply chains that can be resilient to the shocks resulting from economic and environmental changes [25]. This shift is supporting a novel cognitive framework of food-based systems that is data driven, self-educating, and in the process of constant improvement. The new technologies, including digital twins, nanotechnology, and quantum computing are likely to transform the global food system further into an intelligent, interconnected ecosystem. This paradigm resembles the biological neural structures, where the artificial neural networks modeled after the human brain work with advanced algorithms to facilitate decision making and optimization. Figure 1 shows how the agri-food technologies driven by AI will be invested in 2024-2025. The top growth is in food security solutions (52.4), data analytics platforms (47.1), and climate smart agriculture and automation technologies (46.4). These results indicate that the world is investing more in fields such as AI based precision agriculture, biotechnology, robotics, and sustainable food production systems.

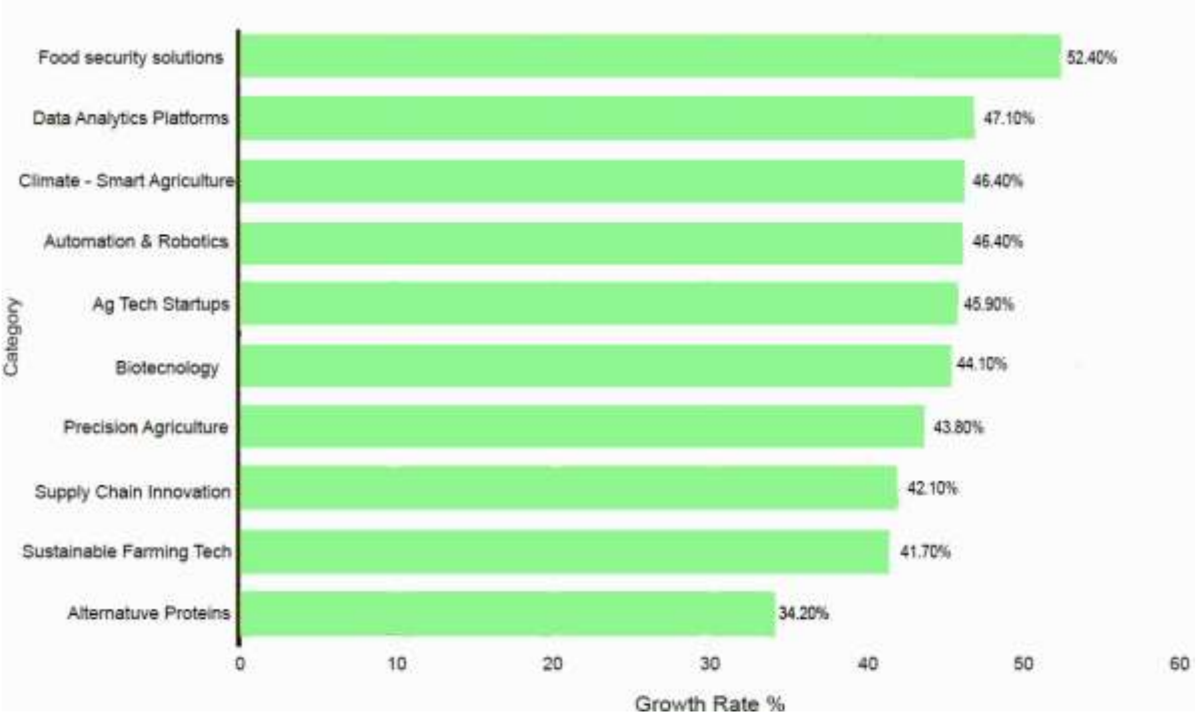

Figure 1. Improvement in AI based agri-food technology investments (2024-2025): Beginning with food security solutions (52.4 percent) and data analytics platform (47.1 percent) and climate smart agriculture and automation (46.4 percent) follow as agri-food technology investment has been growing worldwide in the past.

The review is directed at generalization of the multiple applications of next generation AI technologies (machine learning, deep learning, robotics and IoT) along agri-food value chain [34]. In particular, it investigates the possibility of AI application in improving efficiency, resiliency and environmental leadership in the sector, beginning with precision agriculture and smart farming and food manufacture, processing and supply chain management [35, 36, 37, 38].

Figure 2: AI technologies for smart food production system.

The above applications increase operational efficiency that facilitates food safety, improved resources management and lessening of wastes, which contribute to sustainable agriculture and economic prosperity. Figure 2 is an overview of the profound and far-reaching effects of the AI breakthroughs on different sectors of the food industry. The whole implementation of AI is the secret of the balance between production with the stewardship in the energy and labor that produce food systems in the future, and which have positive effects on society. Figure 3 AI enabled sustainability effect on the main agricultural indicators comparing the present performance with the expected improvements by 2030. The findings indicate that artificial intelligence technologies have brought about major gains in efficiency of resources, waste generation reduction, and carbon reposition, as well as environmental performance as a whole.

This review aims to comprehensively review the current state of AI applications for sustainable food production systems from the processes through to the outputs. It also discusses the technology evaluations of deep learning and computer vision, IoT and sensor networks, ML based decision support systems and agricultural robotics. Sustainability in terms of its environmental impact, resource economics and greenhouse gas emissions are also discussed. In addition, it discusses implementation considerations: the potential production challenges, individual level barriers to use, cost benefit analysis, cost and benefit sharing (even how to scale up). Last but not least, the review discusses about policy and governance. These include regulatory perspectives, data privacy, code of ethics and issues to do with equality (related to information dissemination. Lastly, the review points towards the future through the opportunities for future research, other technologies and recommendations to the right people.

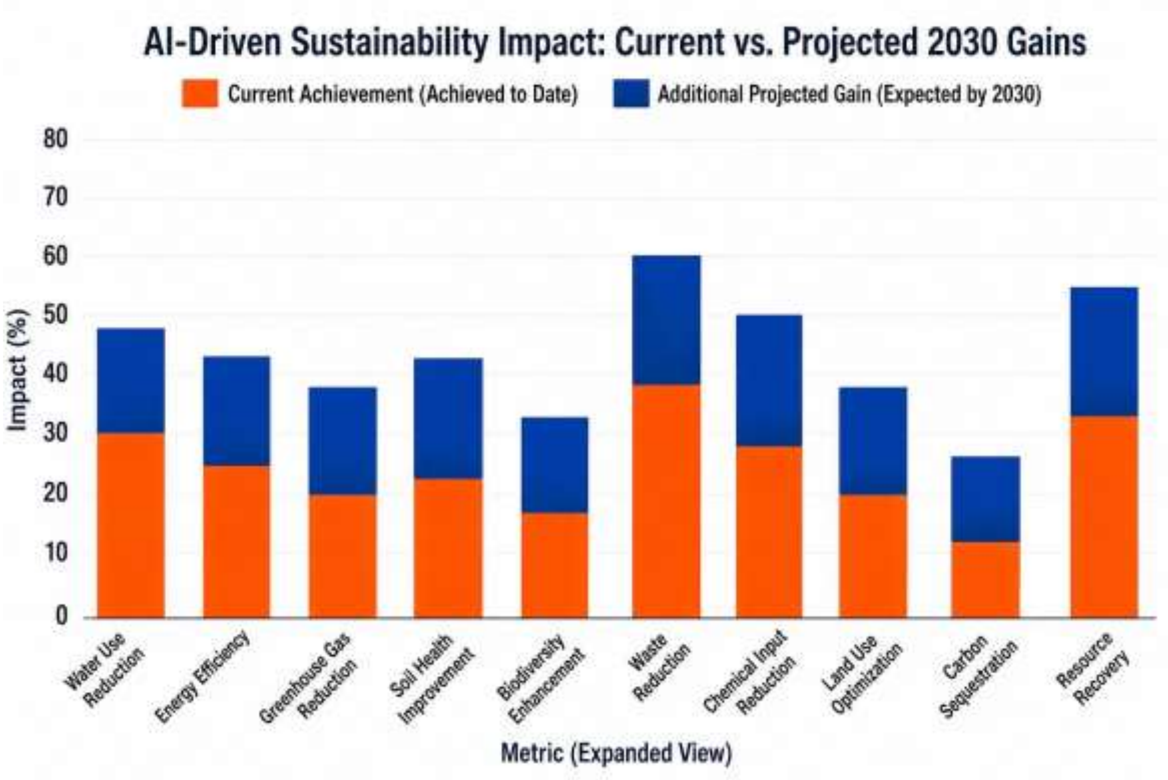

Figure 3. The potential impact of AI on sustainability metrics in agriculture, when it comes to current performance vs. the improvements by 2030, both from a resource efficiency and carbon sequestration perspective and an environmental one.

2. Related Works and Motivations

The development of food production towards intelligent and sustainable paradigm is another area that has shifted to incorporate superior model archetypes such as Vision Transformers (ViTs), predictive analytics, hybrid deep learning frameworks, computer vision and AI-IoT systems throughout the agricultural value chain to be utilized more efficiently, productively, with precision-based agriculture applications and eliminate waste [39]. The Internet of Things (IoT) based sensors, drones, and satellite photography constructions that surround the precision farming strategies to offer early diagnosis plant diseases assistance so as automated decision-making systems which help achieve global food security purpose are also gaining more significance so as to establish confidence in sustainable farming [40][41].

Precision agriculture has become more accurate with the introduction of ViT based architectures such as PLAViT that are more capable of modeling robust long-range dependencies with self-attention mechanics and achieve accuracy levels of over 95% in the case of plant disease classification. The hybrid ViTResNet models and improved vision transformers record higher performances in terms of crop health and texture analysis hence guaranteeing enhanced scalability and faster inferences which would enable real time deployment of the IoT. In addition, when applied together with ViT models, Efficient Net increases the identification accuracy of potato disease by 11.43% in complex field conditions [42]. In our analysis, deep learning technologies have made the process of feature extraction of multispectral images simpler to achieve accuracy targeted pesticide application and site-specific application to achieve sustainability and integration to create a geographic information system (GIS) database that can apply spatially conscious decision systems to eradicate excessive use of chemicals [2][41]. Other aspects that AI technologies can be applied to enhance crop monitoring are food processing, logistics, and supply chain management. Predictive analytics based on blockchain technologies addresses demand and introduces a circular economy solution to reduce the quantity of waste generated in some applications by up to 30% [25][43]. Supply chain optimization through machine learning also enhance the traceability of supplies, enhances food safety, and resilience to disruption. AI IoT robotics systems can facilitate the real time analytics and informed operational decisions throughout the agricultural processes, which leads to the improvement in the productivity and sustainability in a significant way [44][45]. Such innovations are particularly necessary since by 2050, the world will be forced to feed its people nearly 70 times as many people as it does at present [46]. The fields that require predictive analytics are yield forecasting, pest detection, and environmental monitoring, and strategy creation to reduce the risks in agriculture also [47]. Other complementary technologies like blockchain would increase transparency and accountability of food supply chains, contributing to the long term sustainability goals and economic sustainability of farming communities [48,49,50,51,52,53,54]. Such uses in different fields are also reflected in Figure 4, which shows the estimated increase in AI use in the food production sectors in the next 2030, with precision agriculture, smart farming, supply chain AI, livestock monitoring, and food safety systems.

Sustainable environmental management is also achieved with the help of AI enabled precision agriculture that reduces environmental effects and uses agricultural practices and resources more efficiently. This solution combines GPS and IoT sensors with sophisticated analytics to monitor and manage crops and soil in the most precise manner. Gupta showed that remote monitoring and optimization that can be achieved by precision agriculture applications can enhance crop yields by 15% and decrease resource use by 20% [55].

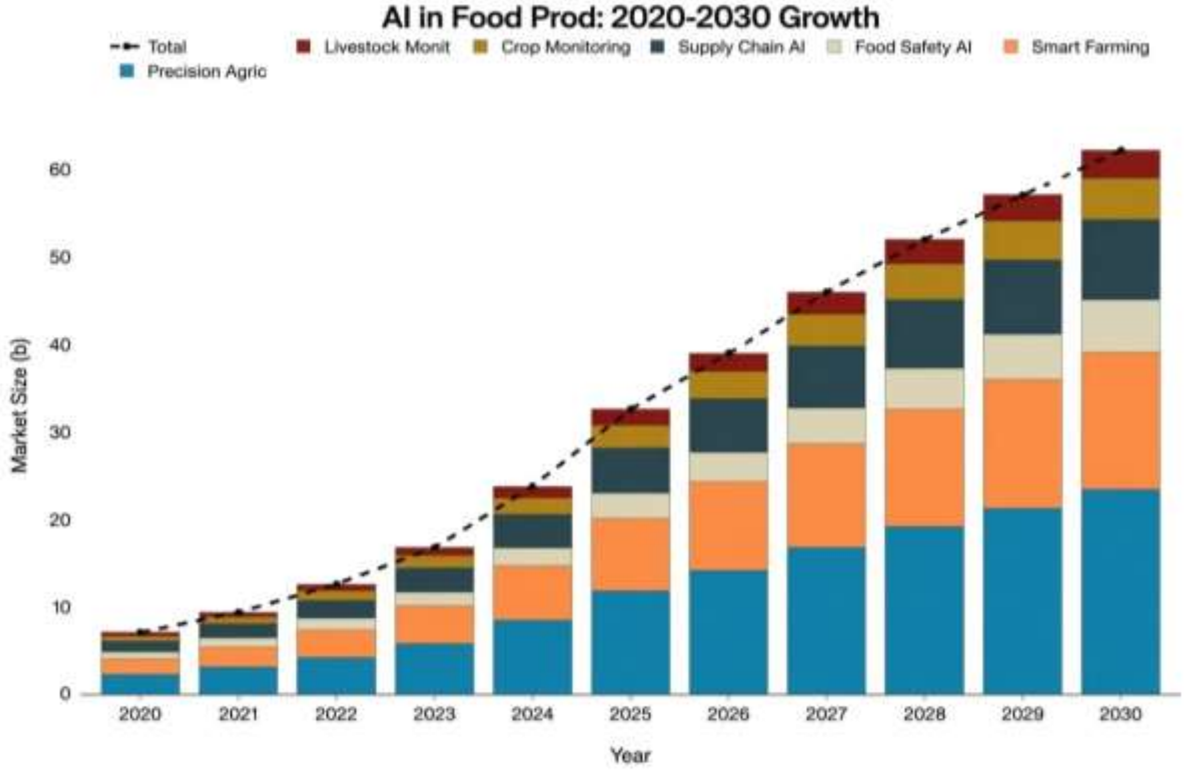

Figure 4. Expansion of AI applications in food production industries between 2020 and 2030 such as precision agriculture, smart farming, supply chain AI, livestock monitoring and food safety systems.

A bibliometric review by Sánchez Castillo has indicated that the application of AI in precision agriculture to enhance resource productivity and minimize the negative impact on the environment is increasingly becoming a significant subject [56]. In a similar vein, San Miguel et al. highlighted that precision farming activities minimize environmental destruction and operational expenditure and comply with sustainability policies like the European Green Deal [57]. Lishchuk et al. also examined the precision agriculture processes of minimizing environmental hazards and enhancing production efficiency of agroecosystems [58]. Other researchers document CO 2 emissions, water consumption and input expenses reduction as a result of AI based resource optimization [59][60]. Marcelo and Clandio analyzed the effect of the environment with the help of life cycle assessment and demonstrated that precision agriculture decreased the eutrophication potential by 60.84, the acidification potential by 31.79, and the global warming potential by 28.65% [61]. Rani et al. have also said that there was an increase in crop yield by 20% and a decrease in the use of water and fertilizer by 40 percent with the application of precision agriculture methods [62]. Moreover, AI powered monitoring systems through sensors, drones, GIS, and predictive analytics enhance the condition of soil health mapping, nutrient management, and climate adaptation planning [63][64]. Intelligent AI based applications like digital twin-based decision systems can predict future plant growth and disease risk in real time with a high accuracy of over 80 percent and autonomous robotic spraying can greatly decrease pesticide and fertilizer use [65].

In spite of all these developments, a number of barriers restrict the large-scale implementation of AI in sustainable food production. Alibašić presented a systems-based approach that was consistent with the European Commission farm to fork strategy, which focuses on economic, environmental, and social aspects of sustainable food systems [66]. Sakapaji and Puthenkalam also raised the issues of data privacy, security, and algorithmic bias and emphasized the importance of establishing ethical principles in AI agriculture [67]. Khadka and Kumar addressed the topic of machine learning, drones, and IoT technologies in agriculture to optimize the process, discovering the challenges to its implementation and considering the environmental factors [68][69]. Equally, Akintuyi studied the adoption of AI in agriculture productivity and sustainability, highlighting integration issues in the farming activities [70]. Boora and Ahalawat noted the need to increase the production of food by 70 percent in 2050 and addressed the constraints in using conventional approaches to farming, as well as the problem of data collection, privacy, and technical stability in AI based systems [71][72]. Almoselhy and Usmani noted the use of AI in food safety, quality control, and tailored eating and highlighted the necessity of interdisciplinary cooperation as an ethical implementation [73]. Markovic et al. addressed sociotechnical obstacles, including data quality, interoperability, and user interaction in AI agri-food systems, suggesting semantic integration and synthetic data generation as the way to enhance sustainability [74]. Abdallah et al. emphasized the role of AI in facilitating a sustainable food processing, packaging, and resource preservation [75]. Joshi studied robotics, automation, and climate adaptive farming, as well as discovered infrastructure gaps and ethical issues related to AI adoption [76]. Keskes studied the use of AI in sustainable fruit production under environmental and economic limitations [77]. Harikrishnan et al. also elaborated on ethical considerations such as algorithmic prejudice, social justice and regulation needed to ensure the ethical implementation of AI in food systems [40].

In general, the integration of AI, IoT, precision agriculture and predictive analytics is a revolution in the field of sustainable and smart food production. These enable site-specific management, improved water and fertilizer use efficiency, reduced costs of operation and enhance climate change adaptability [44,45,46]. However, data management and system limitations, interoperability and ethical considerations remain significant challenges. These challenges can be addressed by researchers, policy makers and industries who should collaborate to ensure equal access, privacy and scalable deployment of AI driven agricultural solutions. These arguments point to the need for more advanced, reliable and explainable AI systems to support sustainable food production and provide solutions to increase food for the growing global population. Figure 5 illustrates the expected evolution of these enabling technologies by presenting the expected penetration of AI driven farming technologies from 2025 to 2030, such as robotics, IoT sensors, blockchain, digital twins, and AR/VR training systems. Furthermore, Table 1 shows the comparison between traditional agricultural practices and next generation AI driven technologies, such as Vision Transformers, in terms of key performance indicators, such as accuracy, scalability, resource efficiency and cost. Furthermore, Table 2 shows a comparison between Pure Vision Transformers, Hybrid ViTCNN and traditional Convolutional Neural Networks (CNN) in agricultural use-cases, highlighting their differences in feature extraction, accuracy and scalability.

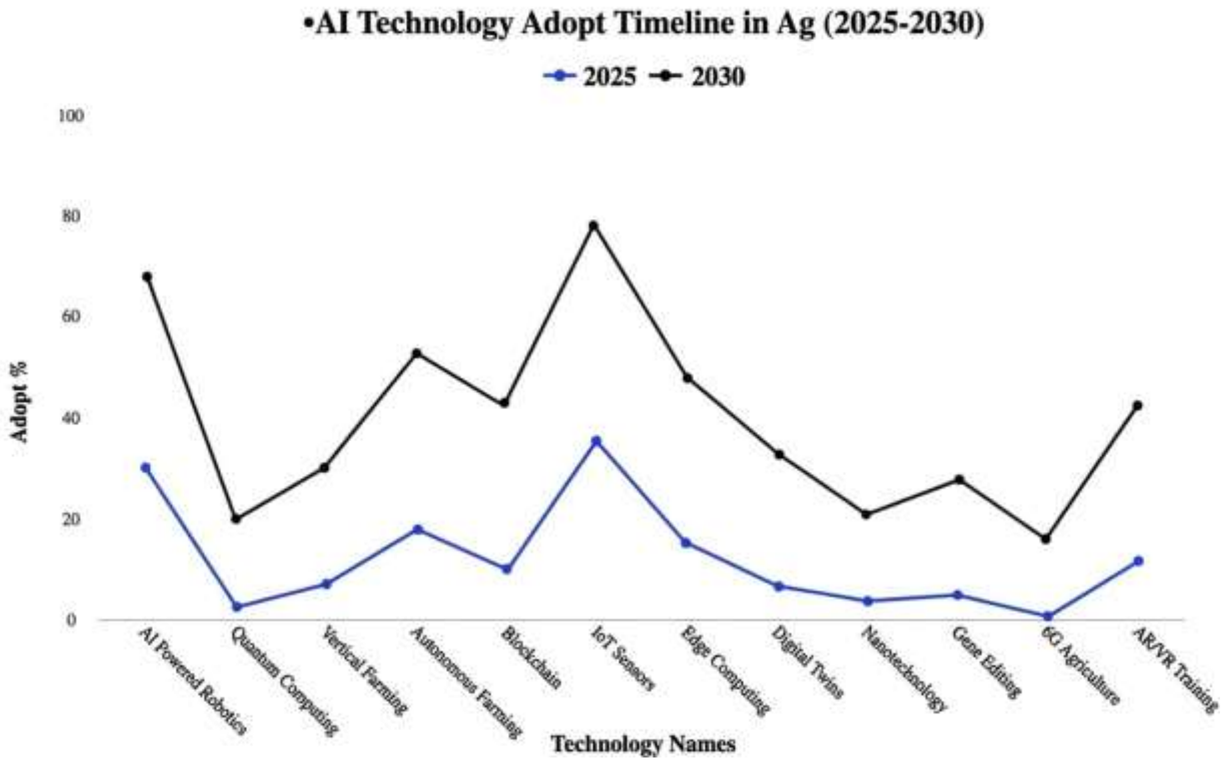

Figure 5. Likelihood of adoption of artificial intelligence driven agricultural technologies between 2025 and 2030 with robotics, IoT sensors, blockchain, training digital twins and AR/VR training.

Table 1. The pros and cons of current agricultural methods vs. AI based technologies in the areas of accuracy, scalability, efficiency and computation.

Aspect	Traditional Methods	Next-Gen AI
Disease Detection Accuracy	70-85%, manual/expert-dependent	95-99%, automated [40]
Scalability	Limited to small farms	Large-scale, real-time IoT [41]
Resource Efficiency	High waste from over-application	20-40% reduction via precision [25] [40]
Computational Cost	Low but labor-intensive	Optimized for edge devices [41]

Table 2. Comparison of Pure ViTs, Hybrid ViTCNN models, and traditional CNNs in agricultural applications.

Aspect	**Pure ViTs**	**Hybrid ViT-CNN Models**	**Traditional CNNs**
Feature Focus	Global context via self-attention	Local textures + global context	Local patterns only
Accuracy in Agriculture	95%+on Plant Village [43]	85-99% on diverse crops [59]	80-90%, less robust [43]
Challenges	High data/compute needs [43]	Balanced fusion strategies [59]	Limited scalable [43]

3. Basic AI Algorithms and Computational Philosophies

The food system transformation is based on extremely advanced AI programs that can process the size, diversity, and time characteristics of agricultural data.

3.1 Deep Learning (DL) Architectures and Machine Learning (ML) Specialization

Deep Learning (DL) methods offer the data processing flexibility that is needed to analyze the complex farming data, which often consists of visual, spatial, and numerical inputs. Convolutional Neural Networks (CNNs) is a major architecture of DL that is useful in processing image data (e.g., drone or vision cameras) to perform tasks like monitoring crop health and identifying pests [78]. DL methods are also useful in predictive modeling, where they are useful to predict the crop production and commodity prices. Moreover, conventional algorithms of Machine Learning (ML) including Support Vector Machines (SVMs) and Random Forests are essential in performing instrumental classification [78][79]. These algorithms are used to conduct correct classification of soil compatibility, evaluate the soil fertility and efficient selection of the crops. Since the agricultural cycles are time based, time series analysis is essential. Farming data can be analyzed using DL algorithms and can be effectively utilized to predict crop yield production and analyze the demand changes of crops [80].

3.2 Autonomy in Control Systems and Reinforcement Learning (RL)

Reinforcement Learning (RL) is one of the most important NextGen AI approaches, characterized by its capability to learn the best behaviors or policies with the help of an environment or a simulator. This renders RL exceptionally adapted to solving intricate, sequential control, and decision-making challenges which characterize contemporary agri-food operations. The RL is used in main areas of the food system, such as agricultural production (e.g., optimizing irrigation and fertilization times), food processing and distribution logistics, and very technical problems, such as genotype selection in molecular breeding [81]. As an illustration in Figure 6, the cognitive systems assist scientists to choose drought and salinity resistant genetic properties through logical analysis of gene maps, thereby hastening the generation of hearty varieties.

Already in the past, the model-based Reinforcement Learning methods have proven useful in autonomous systems, including those implemented in greenhouse automation [82]. The ability of RL to generate policies to maximize expected future reward renders it crucial to realizing actual, closed loop automation in farming.

Figure 6. Genetic engineering and smart seeds when bioinformatics meet agriculture to produce more resilient and efficient crops.

3.3 Explainable and Causal AI (XAI) Imperative

Trust, accountability and transparency are essential for effective, ethical and operational deployment of food security and resource management using autonomous systems. The Explainable Artificial Intelligence (XAI) concept can be used to explain the model that ensures the fair and accountable operation of the system [83]. The most obvious one is the Explainable Reinforcement Learning (XRL) framework that maximizes the performance and explain ability in a two-stage process. During the initial stage, a reinforcement learning (RL) agent is trained to maximize the expected rewards in the food system by means of a control policy. A Structural Causal Model (SCM) is built around the interactions of the agent with a simulator in the second step, and it reflects causal relationships between internal and external variables, which are formulated with the help of a domain expert [81].

XRL framework continuously optimizes the control policy and the SCM until a consistent and understandable result is obtained. The policy that would be arrived at must be in accordance to the causal structure learned so that the decisions made are not made on the basis of strictly statistical correlations. One of the main strengths of sophisticated XRL techniques is generating counterfactual explanations, explaining how decisions would have varied under varying conditions of input, thus improving transparency and fairness [81].

Causal learning and interpretable policy using XRL makes theory practical. This property would be particularly welcome in sustainable food systems, where complex control processes involving optimal irrigation strategies, resource allocation and crop yield must be explained. As a result, XRL will allow the shift between predictive to causal policy suggestions maximizing performance without violating the environmental and operational limitations.

4. Smart Production Systems: Accurate Agriculture and Resource Management

The concept of AI is leading to the development of precision agriculture because it is turning farming into a highly site-specific operation, predictive and continuous.

4.1 AI to manage crops and improve yields optimally

Smart farming uses AI to proactively respond to current sustainability issues in agriculture [80]. AI is used to synthesize useful real-time intelligence based on heterogeneous data sources such as satellites, drones, remote sensors and smart farm equipment to provide the complete picture of the soil conditions, weather patterns, and crop health. This intelligence can enable farmers to make informed choices about crop choice, crop cycle optimization, and the right time to perform activities, including sowing, composting, and harvesting [84]. AI directs site-specific interventions based on an analysis of feature importance. As an agronomist, it is possible to use the outputs of the models to focus on the important parameters, e.g., the pH of the soil or ambient temperature, and provide guidance on the choice of crops and soil preparation. With such a detailed analysis, it becomes possible to allocate inputs to specific regions; those areas that are found to have predicted nutrient deficiencies can have the optimized fertilizer applications so that the overall resource wastes are reduced and at the same time yields optimized [85].

4.2 Smart Irrigation with Deep Learning

Water stress in combination with climate change are the two-fold most important global challenges that require accurate and efficient irrigation management. This is an area in which DL plays a pivotal role in converting the framework of irrigation management from the traditional wisdom based to precise prediction models. The DL models indeed have distinct advantages in water management such as spatial identification of water needs, accurate prediction of soil moisture, and hydrology of the future. In the real world, hybrid DL usually show a superior performance as they are able to incorporate different model and data types.

4.3 Enabling the Shift to Regenerative Agriculture

The co-integration of AI technologies provides the needed analytical and control framework to enable transition to truly regenerative agricultural systems. Leveraging the intelligence of AI, conventional high intensity practices such as intensive farming units, monocropping and the indiscriminate use of chemical fertilizers can be phased out in favor of more complex forms of regeneration [84]. AI models are instrumental in analyzing the efficacy of these new methods, assisting in the delineation and measurement of sustainable objectives alongside the traditional goal of improving yield potential.

4.4 Time as an Operationalization Continuous Control Systems

The conventional to precision agriculture hedge is actually a change of time horizon of operation. Irrigation and environmental control require the capacity to make interventions in a timely manner, if not instantaneously. The time it takes to complete a control loop is what makes resource management possible. The technologies of Edge to cloud Collaborative architecture are created to decrease the response time by several minutes to several seconds [86]. This improvement on the infrastructure is highly significant since it will transform agriculture, as a batch process, into a real time, high frequency closed loop machine.

5. Smart Systems Integration and Operational Infrastructure

The agri-food value chain needs physical infrastructure and resilient computational infrastructure to scale AI solutions throughout the agri-food industry.

5.1 The Convergence of IoT, Sensing, and Robotics

The trend in the industry is to consider more advanced convergence, wherein partnerships between Agri Tech providers, robotics firms, and food automation firms become a source of full, end to end smart systems. This methodical combination raises transparency throughout the whole pathway of farm to the fork due to the smooth connection of the Internet of Things (IoT), diverse sensor modalities, and improved vision technologies [87]. The recent literature demonstrates the important developments in smart sensing technology that are used in arable crops and grasslands. These systems use a variety of types of sensors, such as optical, acoustic, electromagnetic and special soil sensors. Together with machine learning algorithms like SVMs, CNNs, and Random Forests, these sensors are used to optimize field level strategies that are important, including fertilization, irrigation timing, and the accurate pest management [78]. These multi domain sensing modalities are being rapidly developed and integrated out of necessity of high resolution, multi domain data collection. Table 3 is a summary of the critical sensor AI integrations that are driving the contemporary precision agriculture.

Table 3: The Integration of AI and Sensing Technologies in Precision Agriculture

Sensor Type	AI Technique(s) Used	Agricultural Application Focus	Critical Operational Outcome
Optical Sensors (Drones, Satellite)	Deep Learning (CNNs)	Crop health monitoring, pest/disease detection, field-level biomass assessment	Data collection for smarter decisions on where/when to grow; replacing blanket application [84]
Soil Sensors	Machine Learning (SVMs), Deep Learning	Soil fertility classification, soil water content prediction	Input allocation optimization; precise fertilizer and irrigation scheduling [86]
Acoustic/Vision Systems	Machine Learning, Image Processing Fusion	Real-time monitoring of crop condition and environment	Enhanced transparency; enabling automation and robotics (e.g., automated harvesting) [78]

5.2 Scalability and Resilience Distributed Architectures

Distributed architectures are needed to address the limitations of connectivity and latency that tend to be a major issue in large rural regions [78]. The edge AI that enables complex inference and processing to be executed locally prior to data transmission is essential to supporting the low latency needs of control system applications, like intelligent irrigation in real time [86]. This enables local processing, improving robustness and reducing the reliance on the high-speed, frequent links. In addition, the intricacy of the integrated systems also demands advanced governance that can cope with the massive and sensitive data generated. Distributed data governance is being proposed in blockchain systems to enable transparency and help them build equal data ownership and data privacy regulations [78].

5.3 Interoperability Crisis in the Design of Ecosystems

A mapping of the variety of sensors and the desire to build fully integrated smart ecosystems, as seen above, reveals a technological and business bottleneck: interoperability [78]. While the proliferation of specific hardware (drones, sensors, automated platforms) is delivering detailed information, the market is very fragmented, with closed systems and variety of data formats used to exchange information, a strong constraint to the rollout of AI solutions from ad-hoc pilot studies. This problem is compounded by the lack of infrastructure and connectivity [78]. Thus, the emergence of standard data model and opensource community is becoming a critical factor. This data integration and exchange problem is also linked to the potential of AI to play out across the value chain.

6. AI in Post-Harvest Management, Processing, and Supply Chain Resilience

AI is well applied across the stages of processing, distribution and consumption within the food system, to help ensure quality, safety and reducing food waste.

6.1 Optimization and Safety of AI in food processing

The AI offers a groundbreaking advantage to the food processing sector because it is capable of improving food safety, quality assurance and sustainability in a systematic way. With the inclusion of AI, the industry will be able to streamline the complex production processes and waste can be drastically decreased. This transformational power assists in overcoming underlying issues to do with food security [88]. To be on the safe side, sophisticated models are used to check the integrity of supply chain. As one of them, a model of dynamic unsupervised anomaly detection based on Bayesian Network (BN) has been proposed to forecast when drastic shifts in the domains associated with the food supply chain could cause food safety issues [89]. It is expected that the analytical integration of image processing technologies with shallow and deep machine learning models will open up significant opportunities in quality control and hazard detection throughout food processing and distribution [90].

6.2 Cold Chain Integrity and Supply Chain Logistics

AI is essential in ensuring the integrity of food during transportation and storage. AI is increasingly being used together with IoT sensors to monitor environment variables (e.g., humidity, temperature and storage conditions) throughout the supply chain in real time. This active supervision makes sure that the perishable products are well preserved, spoilage significantly decreases and food wastage is minimized before food reaches the consumer. Apart from physical tracking, regulatory compliance is being made easier with AI platforms. Using information on real time inspection, quality control and regulatory adjustments, AI platforms will be used for regulatory reporting. The capability has a great impact in alleviating the administrative load in companies as well as ensuring that companies are consistently compliant with the changing global safety requirements. Moreover, blockchain technology, along with AI, boosts supply chain visibility and offers unaltered provenance and condition records [91].

6.3 AI for Circular Economy and Waste Minimization

AI technologies are essential tools to enhance sustainable waste management and support circular economy projects. The algorithms of AI are used to optimize the procedures of gathering, transportation, sorting, and recycling of different wastes. In particular, AI can track information about industrial processes and products, which will enable the correct evaluation of the state of an item and its reuse, or monitor its surroundings to identify the possibility of recycling. The general outcomes of the implementation of AI in these projects are very encouraging, showing the possibility to increase energy efficiency, decrease the total waste, optimize the use of resources, and decrease the environmental impact throughout the supply chain. It is believed that further investment is essential to realize the full potential of these AI circular economy models in the world [92].

6.4 AI as a Regulatory and Risk Management Tool

The use of AI in supply chain management represents a shift towards more than mere operational efficiency to more advanced regulatory and risk management. AI systems can de risk the global food supply chain by automating compliance reporting and constantly aligning real time operational data with fluid regulatory requirements [91]. This feature makes AI not only a tool of technology, but also a cornerstone of corporate governance and compliance strategy. Firms that take advantage of such degree of operational transparency have a competitive advantage based on the reduced legal liability and financial risk in case of food safety failures and recalls. As shown in Figure 7 Smart supply chain solutions, including harvest to distribution, use predictive analytics and advanced logistics to minimize postharvest losses, maintain product quality, and enhance the efficiency and sustainability of food delivery networks.

Figure 7. Intelligent supply chains reduce post-harvest losses and improve sustainable food distribution.

7. Future Foods, Ingredient Design, and Accelerating Innovation

AI offers a profound transformative path to address the challenge of creating highly nutritious and sustainable foods while sharply minimizing environmental footprints [93].

7.1 AI in Food: A Discovery and Design Field

The historically slow, fragmented, and empirical food innovation can be defeated by embracing AI as Food as an emerging, predictive field. The field combines new techniques throughout the product pipeline, including ingredient design, formulation development, fermentation and production processes, accurate texture analysis, sensory properties (flavor mapping), manufacturing optimization, and recipe generation. Initial achievements in this field show that AI can forecast protein behavior using molecular composition, precisely map chemical structures to the corresponding flavors, and customize consumer experiences using predictive models [93]. This is essential in hastening the creation of sustainable protein systems and alternative foods, including plant alternatives to resource intensive meat, dairy, fish, and egg products [84]. AI offers the means to rapidly iterate and develop complex alternative ingredients.

7.2 Innovation Infrastructure Strategic Priorities

Strategic changes in infrastructure and research philosophy are needed to realize the full potential of AI in food innovation. One of the main suggestions is that a fundamental conceptual change is required: food should not be viewed as a raw material, but as a programmable biomaterial that can be engineered and designed accurately. This philosophical shift must be supported by automated discovery infrastructure. The research and development processes need to be automated by constructing Self Driving Laboratories (SDLs) to shift the industry to a predictive, design science of food [93]. Moreover, AI facilitates responsible exploration and safe scaling of diverse new food technologies that are essential to nourish a growing population, such as functional foods, synthetic biology uses, and 3D food printing, and carefully scrutinize their conservation, safety, nutritional, sensory, and welfare issues [94].

7.3 The Secret to Breakthroughs is Multimodal Data

The ability to correlate a variety of, disparate data types: chemical structure, molecular performance metrics, high resolution sensory evaluation and manufacturing efficiency data is critically important to achieve the ambitious goals of AI food design, including predicting performance based on molecular composition or mapping specific molecules to sensory flavor outcomes. This necessitates advanced data architectures. Nevertheless, one of the major issues is the lack of standardized, multimodal data and the overall lack of standardization in the industry [93]. Thus, the most urgent research frontier is not merely model development but the architectural challenge of developing integrated, standardized databases that can easily connect these diverse domains. This data standardization is the foundation for predictive automated food design and rapid uptake of sustainable protein production systems.

8. Barriers to Strategic Implementation and Systemic Challenges

The technological leap is amazing, but for large, fair and ethical use of NextGen AI systems there are many systemic issues to be addressed.

8.1 Data, Model, and Generalization Limitations

One of the main limitations of implementing AI in agriculture is the problem of data standardization and centralization, which is a major limiting factor in the training, generalization and transferability of models at different levels of crop species, climate and regions. Existing models are usually limited to generalization, and are hard to adapt to a variety of climatic conditions, and are computationally intensive. To overcome the lack of data and enhance resilience, the future studies should focus on the development of more sophisticated distributed learning techniques, including federated learning and few shot learning [93]. Moreover, due to the growing instability of weather patterns in the world, there is a dire necessity to concentrate research on specialized climate adaptive models that are specifically aimed at managing and responding to extreme weather events [86].

8.2 Gaps in operation, economic, and infrastructure

The initial capital expenditure on the infrastructure of the sophisticated sensing, robotics and integrated data platforms is a major barrier to adoption especially to small farms and less developed economies. Combined with the cost of application these costs and barriers to application due to regional adaptability and acceptance by farmers endanger fair access to smart farming tools. Rural connectivity still hinders the implementation of complex systems with low latency needs like automated irrigation control [86]. Solving the problem of labor shortage and technology transfer is also a priority. The major players, such as the World Bank, the United Nations Educational, Scientific and cultural Organization (UNESCO) and USAID, are instrumental in offering specific funding, capacity building programs, and technology transfer systems to the low-income countries (LICs) to embrace the contemporary ideas of agriculture like precision farming [95].

8.3 Ethical, Regulatory and Societal Obstacles

Implementation of autonomous AI must be strictly focused on ethical aspects. Addressing the anxieties that relate to transparency, privacy of data, and the critical question of equitable data ownership are the most important factors towards mass adoption [78]. In addition, the lack of consumer confidence and minimal barriers to acceptance is a current issue particularly in the context of new food ideas and products that are produced using synthetic biology or highly autonomous production approaches [93]. XRL and its focus on causal modeling and counterfactual explanations provides a requisite mechanism to the issue of transparency and the development of justifiable systems [96].

8.4 Technological Accelerator: Policy Intervention

An in-depth examination of systemic barriers shows that most of these key constraints include high costs, equitable access and data ownership issues are not technical issues but are inherently institutional and policy failures. The policy interventions are clearly required to guarantee equitable ownership of information, create interoperability standards, and guarantee equitable access to smart farming tools [78]. This conclusion implies that institutional adaptation, rather than technological invention, can be considered the real Next Generation challenge of the agri-food system. The greatest leverage points in terms of maximizing the societal and environmental impact of AI advances that have been shown to be successful in laboratory environments include policy decisions such as supporting the standardized data marketplaces or investing in rural connectivity infrastructure. Table 4. offers a methodical view of these barriers along with the strategic mitigation measures that need to be undertaken.

Table 4: AI adoption agri-food systems systemic barriers and strategic mitigation to AI adoption.

Category of Challenge	Specific Barrier Identified	Impact on System Adoption	Proposed Future Research/Mitigation
Data and Methodology	Lack of standardization; scarce multimodal data; poor generalization ability	Constrains model training efficiency and limits geographical scalability and innovation (e.g., ingredient design)	Federated and Few-Shot Learning; treating food as a programmable biomaterial [86]

Technical and Infrastructure	High infrastructure costs; limited interoperability; rural connectivity constraints	Restricts equitable access and prevents necessary real-time processing and closed-loop control	Emphasis on Edge AI for local inference; policy intervention for infrastructure development [86]
Ethical, Governance, and Trust	Low consumer confidence; lack of transparency; data privacy concerns; unclear data ownership	Hinders rapid industry transfer, public acceptance, and necessary global collaboration	XAI frameworks (e.g., XRL, SCMs); Blockchain for decentralized data governance [81]
Socio Economic and Policy	Labor scarcity; need for technology transfer (LICs); governance frameworks lagging technology	Exacerbates yield problems; creates global inequity; slows responsible large-scale deployment	Targeted funding by international organizations (UNESCO, World Bank); policy interventions for fair data access [95]

9. Healthier Food Solutions Innovative Strategies

Healthier food solutions are innovative strategies that involve numerous approaches that help to enhance the health and sustainability of the food system of the population. These are product reformulation strategies, technology development and joint stakeholder efforts. These innovative strategies highlight important features as discussed below [97,98,99].

9.1 The use of Big Data and Artificial Intelligence to develop Next-Generation Nutrition Science

The increasing adoption of Big Data and artificial intelligence is causing significant shifts in nutrition science, particularly as it shifts towards more specific and tailored dietary advice. The current AI solutions can handle extensive and diverse amounts of data, allowing one to provide personalized advice, track nutrition in real-time, and reinforce food safety. Another way in which these technologies can assist in enhancing dietary assessment is by taking into consideration image recognition and motion sensors to minimize errors and records details about food types, portion size, and overall nutrient intake [100]. Simultaneously, Big Data analytics is crucial in transforming raw nutritional data into comprehensible information, especially when sophisticated algorithms are used to integrate genetic, metabolic, and lifestyle information to enhance recommendations [101,102]. In addition to human nutrition, AI and Big Data are also becoming useful in enhancing sustainability in animal feeding systems with advanced modeling methods with most of these findings providing insights that can be valuable in enhancing human nutrition studies too [103]. With the encouraging developments, such problems as the safety of personal information, transparency in algorithms, and fair access to these technologies still require a solution to enjoy the full potential of these technologies [104]. All in all, further cooperation among researchers, healthcare practitioners, and technology creators will be crucial to unlock the full potential of AI and Big Data in helping all people with nutrition and health [104]. And, AI is increasingly playing a role in supporting clinical decision-making and interventions towards dietary-related diseases, including obesity and type 2 diabetes [105]. AI's capabilities to offer personalized advice and feedback increases compliance and motivation. However, challenges such as data, algorithm transparency and potential biases remain. Ethical considerations, multidisciplinary approaches and promoting access will be crucial for safe and effective use of AI technologies in nutrition [106].

9.2 Automated Food Production Using Robotics and 3D Printing

Robotic and 3D printing technologies for automated food production are revolutionizing the food manufacturing sector by offering high precision, high efficiency, and high customization. Cooperative robots handle different ingredients and allow the creation of foods with intricate textures and flavors [107]. The use of fully automated systems also simplifies the entire process from feeding materials to printing, processing and packaging, while minimizing downtime and increasing efficiency. The technology offers nutritional control by integrating multiple ingredients to tailor food to specific dietary requirements, and includes functional ingredients such as probiotics to enhance nutrition and prevent food waste [108]. The increasing demand for tailorable and environmentally friendly foods has helped drive the growing 3D food printing market, which is estimated to grow by 55% annually, driven by ongoing improvements to printing technologies and properties of materials [108]. Besides enhancing efficiency and personalization, 3D food printing reduces food waste and cooking time. The continuous evolution of food printers has led to improved nutritional control and quality, signifying the advancement in food manufacturing [109]. Furthermore, this approach is also beneficial to smart agriculture and advanced food processing by improving resource efficiency, sustainability and personalized nutrition [110]. However, there are still some issues to be addressed, such as the technology's cost, complexities and regulations, to promote the use of 3D printing in food industry. The increasing need for individualized and attractive foods, such as in medical applications, space exploration and dietary restrictions, has also driven 3D food printing growth. It offers control over the shape, color, texture, taste, and nutritional value of food, improving processing and food eating experience [109].

9.3 Smart Sensing Systems of Real-Time Ingredient Profiling

Smart sensing ingredients profiling can be used to improve the quality and safety of food by exploiting the use of the advanced technologies to monitor and analyze the properties of food accurately and timely [111][112]. These systems are a combination of various sensors and machine learning algorithms to offer accurate evaluations of food quality, which is especially crucial in dynamic settings like the food supply chain [112]. Some of these systems include the intelligent flavor sensing systems, which replicate human olfaction and gustation to control and optimize the fermentation of foods. They use electronic noses and tongues to detect flavor profiles in real-time, enabling non-destructive and contamination-free measurements, and also employs sophisticated methods of analyzing changes in flavor, such as gas chromatography-ion mobility spectrometry and nuclear magnetic resonance to examine variations in quality [111]. IoT systems based on AI are also important, where convolutional neural networks can be used to monitor food quality over the supply chain with high precision and versatility to make reliable measurements even in challenging environments [112]. Moreover, electronic noses and eyes, powered by bioinspired systems, are used to simulate human sensory perception to determine food quality. Such systems combine gas and image sensors with deep learning algorithms to analyze the data and make informed decisions and multimodal data fusion improves classification [113]. In addition, self-adaptive monitoring systems can modify their functions based on the changes in the environment that allows predicting the quality of food and its shelf-life, minimize the amount of waste, and enhance safety [114]. Although these intelligent sensing systems have enormous potential in terms of enhancing the existing supply chains, there are still issues regarding the seamless integration of these systems into the existing supply chains and the scalability and cost-effectiveness, which underlines the need to do more research and development in order to achieve maximum advantages of the systems in the food industry.

Real-time quality monitoring is required as fresh foods are very perishable during harvesting, storage and transportation and thus it will be necessary to prevent losses and ensure safety. More current developments in intelligent detection methods such as computer vision, electronic noses, and hyperspectral imaging provide useful solutions to monitor quality variations and assist in managing the entire supply chain in a more efficient manner [115]. Interest in using the sensing technologies within the areas of food science and agriculture is growing because of the diverse applications that the technologies can be deployed. These technologies can be used with data analysis techniques (chemometrics) to be much more effective. Nevertheless, there is an industry gap in terms of knowledge and training on these technologies. Practical implications of developing and implementing applications that integrate sensing systems with chemometrics, and that overcome issues in model building and validation. It is important to derive meaningful information out of the data, as Figure 8 demonstrates that sensing technologies and chemometrics can be used to assist each other in converting raw data into actionable information [116].

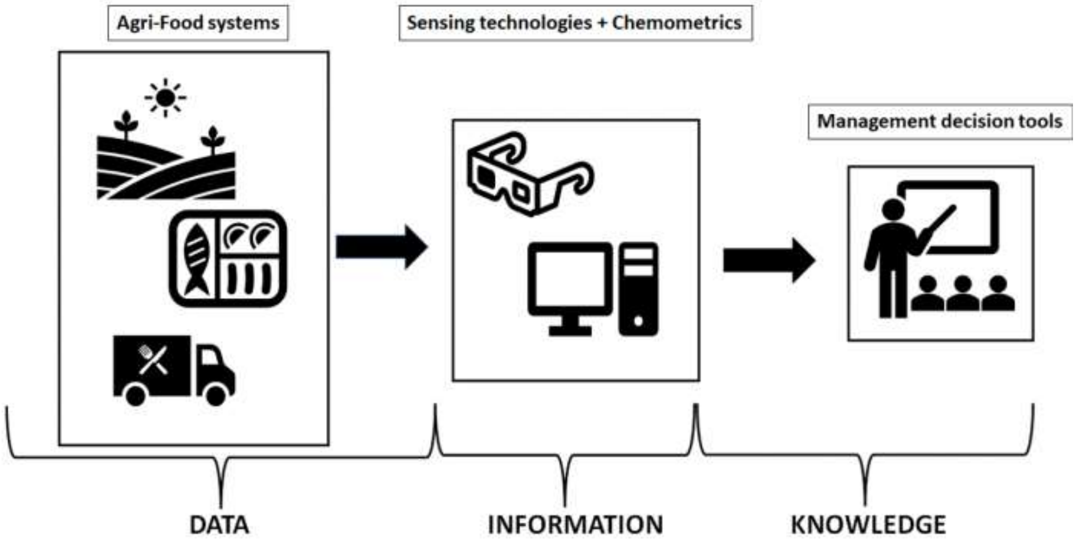

Figure 8. The combination of sensing technologies with chemometrics moving from data to information and knowledge [117].

The conventional milk quality control is usually slow and, in some cases, inadequate to influence the efficiency and quality of products particularly in developing nations. Real time monitoring and quick decision making is required. Application of edge computing and multi spectral sensing in the enhancement of milk quality control through rapid and precise estimation of important parameters like the protein and fat content [117].

9.4 Digital Twin Applications for Efficient Food Formulation and Stability Analysis

Digital twins are transforming the food development by developing virtual models that mimic the properties and behavior of food. They allow quick modification of recipes with the changes of ingredients or consumer requirements, enhancing the nutrition and quality. The models are able to customize food according to personal dietary needs, taking into account such factors as health condition and history [118]. Digital twins can forecast food quality changes and possible spoilage by integrating real time data with machine learning, which can assist in reducing waste [119]. The combination of old-fashioned food science and data driven methods helps to gain insight into the factors influencing stability [120]. A digital twin is generated using machine learning and AI based on the production and other pertinent data, including scientific models, process data and raw material data, to provide traceability and track food status. The digital twin, as illustrated in Figure 9, such as in dairy products like cheese, obtains sensor, machine and processing condition (e.g., temperature, pressure, pH) data and combines it with raw material data, customer complaints, and information on experts. Using the simulation techniques of chemo physical models and numerical food science, the digital twin offers information about the real production process and helps to provide real time feedback. The simulations are also useful to forecast the impact of processing conditions on the product and thus to perform both retrospective and prospective analysis of the product quality and process performance [121]. Although integrating and modeling biological processes might have difficulties with data, resolving such problems is essential to take full advantage of digital twins in food production [122,123,124].

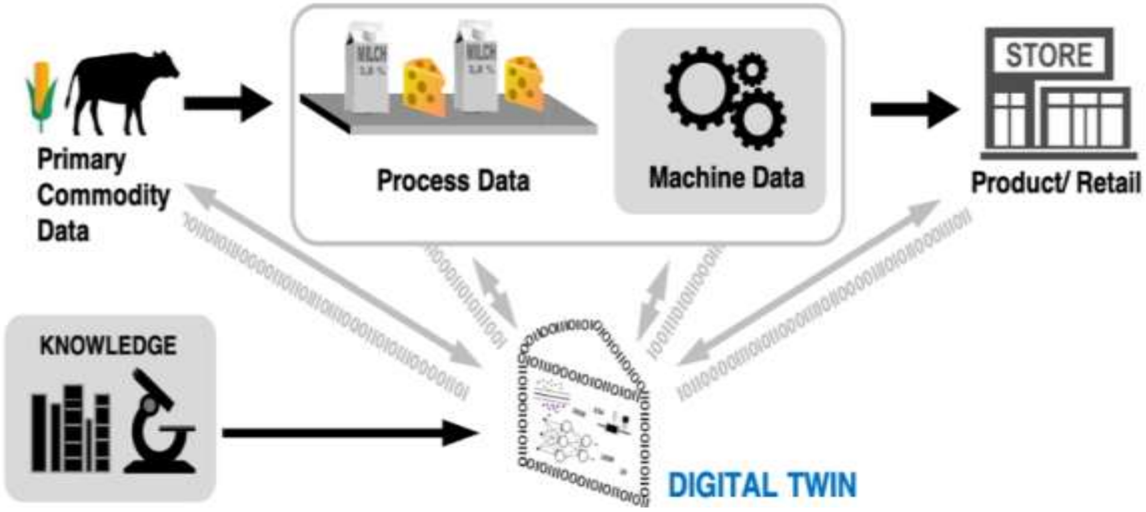

Figure 9. The digital food twin which integrates the data from various sources [120].

9.4.1 Precision Farm Management and AI-Enhanced Digital Twins

Precision farming has been revolutionized by AI powered digital twins that enable farmers to maximize the use of their farm through real time information. These virtual models of real farms are based on AI, IoT, and machine learning to enhance productivity, use resources more effectively, and facilitate sustainable farming. This means that farmers can grow larger crops, minimize waste and environmental degradation by carefully tracking crops and automating their management decisions. As an illustration, digital twins, which are AI powered, can increase crop yields by 15-20% and reduce the use of resources by approximately 25% [125]. They facilitate accurate irrigation, fertilizing and pest control, which conserve water, fertilizers and pesticides [126]. Real time monitoring also enhances the quality of crops and their uniformity which further boosts the overall productivity [127]. Digital twins in agriculture have been associated with a 20 percent reduction in carbon emission in terms of sustainability [125]. Using agrochemicals is optimized with the help of AI and causes less harm to the environment [128]. Virtual simulation enables farmers to experiment and optimize practices prior to their use in the field, facilitating sustainable agricultural practices in the long term [129]. Although these are the advantages, digital twin systems are complicated and demand robust data management and processing capacities [126]. The combination of AI and IoT can also create additional possibilities, including smart irrigation and predictive analytics, which can further improve precision farming [129]. Altogether, AI boosted digital twins have huge potential in enhancing the efficiency and sustainability of farming, but their benefits should be carefully managed, and technological advancements should enhance them.

9.5 Smart Agricultural Systems and Smart Manufacturing

Smart manufacturing and smart farming systems are transforming the industrial and agricultural worlds by enhancing productivity, efficiency, and utilization of resources in a sustainable manner. Combining technologies, including IoT, artificial intelligence, and big data analytics, these systems simplify operations monitoring, resource management, and solving issues such as disease control and performance optimization particularly in poultry farming and more extensive farming activities. Their increasing use indicates a move towards more accurate and data-driven solutions that help make decisions and manage the farm overall better. These systems have important applications and advantages that are summarized as follows [123,125,126,127].

9.6 Precision Agriculture and Smart Sensor Technologies

Smart sensor technologies play a key role in precision agriculture for improving the efficiency, productivity and sustainability of agriculture. These sensors link with the Internet of Things (IoT) and data analytics has given farmers the ability to monitor the condition of their crops, conserve resources, and better inform their decision making. These technologies include temperature, moisture and nutrient sensors, remote sensing devices like drones and satellites that also provide a high-resolution view of the farm [129,130]. Wireless sensor networks also enable free data flow and remote operation of agricultural operations. The benefits of smart sensors in practice include reducing water, fertilizer and pesticide wasted, increasing yields by providing responsive management and supporting sustainability through efficient irrigation and minimizing chemical runoff. But there are also challenges including operational and maintenance costs, difficulty of access in remote area, and compatibility of sensor platforms across different platforms. Future directions will focus on developing cheap, biodegradable sensors and use artificial intelligence to conduct improved data analysis [130]. Intelligent sensing systems using IoT are also finding application in proper monitoring and identification of human activities within the indoor settings. These systems can be very accurate and strong in classifying activities due to their combination of deep learning-based feature extraction with optimization. These examples illustrate the extended possibilities of IoT and intelligent sensing that can be utilized not just in smart homes and healthcare but also to streamline the processes in smart manufacturing and precision agriculture [131].

9.7 Predictive Data analytics to optimize Agricultural Inputs

Predictive data analytics has turned out to be a vital tool in enhancing agricultural inputs in order to boost productivity and sustainable farming. With machine learning applied together with precision agriculture tools, farmers have a better opportunity to control their water, fertilizers, and pesticides, as well as enjoy more accurate yield prediction and faster identification of pests and diseases. Research has revealed that some models, including Support Vector Regression, Random Forest, Decision Tree, and K-Nearest Neighbors can be used in predicting crop yields based on environmental conditions such as rainfall, temperature, and soil nutrients, among others, to enable farmers and policymakers to make sound decisions [132]. Moreover, field management is improved through the use of advanced sensors, mapping based on GPS and real-time data analysis to give accurate information on the soil moisture, nutrient content, and weather conditions, which ultimately benefits the operational cost and better resource allocation [133]. Predictive analytics also aids in improved planning as it provides information on the time to harvest, pest risks, and disease outbreaks. Nonetheless, even with these merits, there are still multiple obstacles, especially in areas with poor access to data, technology, and technical skills that need to be overcome to achieve wider use of predictive analytics and enhance agricultural sustainability and food security [134]. Alongside the significance of using Precision Agriculture practices, wireless sensor networks, and artificial intelligence to improve the resource efficiency and the overall productivity of the agricultural industry [135].

9.8 Robotics Intelligent System of Automated Field Operations

Rapidly, intelligent robotics is transforming field operations in wide-ranging industries including agriculture, oil and gas, and manufacturing using a combination of artificial intelligence and machine learning to enhance efficiency and safety as well as overall performance in harsh environments. Robots in agriculture can be used to address the issue of labor shortage and assist in planting and harvesting [136], whereas automation can be used to streamline the working process, increase productivity, and achieve lower operational expenses. These are facilitated by a variety of aerial and ground robotic systems that are meant to facilitate agricultural processes [137]. AI powered robots can be used in the oil and gas sector to improve the decision-making process and operational performance, as well as perform risky tasks that otherwise would be dangerous to employees [138]. In the industrial context, intelligent robotic technologies are more adaptable and can produce higher-quality products because of the opportunity to adapt to changing production requirements, and the successful implementation of sensors and control algorithms is a prerequisite [139]. Although these benefits exist, implementation cost and data security are some challenges that are still limiting more extensive adoption [140] and as such, to maximize the potential of robotics in field operations, it is necessary to overcome these challenges.

10. IoT Sensor Dynamic Product Quality Monitoring

The use of Internet of Things (IoT) sensors in food product quality monitoring solutions has emerged in recent years as a disruptive innovation to safeguard food safety and quality, minimize wastage and improve consumer confidence. Here, we provide a summary of human centered insights from some research studies that discuss the dynamic application of IoT sensors for tracking quality of food products.

10.1 Real time Food Quality Prediction and Freshness Monitoring using IoT

Some research has focused on developing IoT systems for real time quality monitoring and prediction of food quality during storage and transport. Xu et al. proposed an intelligent model to predict the quality of fresh chicken during cold chain shipment involving the application of flexible humidity and gas sensing in packaging design. This system was capable of continuously monitoring environmental conditions and in accordance with knowledge-based rules and machine learning (ML) algorithms predicted quality loss with an accuracy greater than 90%. This nondestructive approach enables pro-active measures to be taken and it also reduces wastage [141]. Similarly, Islam et al. built a low-cost food monitoring system which integrates a number of sensors - temperature, humidity and gas - and machine learning algorithms for determining freshness. The system gives real time notifications via a mobile application when food is about to go out of shape. The use of experimental testing of various food products showed high prediction accuracy and indicated that the system could be applicable both in the home and commercial settings [142].

In a different study, Popa et al. came up with a homebased IoT monitoring platform specifically made to monitor vacuum packed foods. The system employed low-cost sensors to monitor temperature, humidity, pressure and gas emissions that are related to spoilage. The system was tested on onions and was able to identify gas changes due to deterioration. The method is especially appropriate in daily applications, such as those that cater to geriatric or other vulnerable groups [143] due to its low cost and simplicity.

10.2 Harmonious IoT-AI Systems to adoptive food processing and monitoring supply chains

In addition to freshness prediction, new studies have investigated adaptive IoT-AI systems that can dynamically optimize production and supply chain monitoring of foods. Hussain suggested an intelligent bakery quality assurance system, which combines IoT sensors and adaptive machine learning algorithms to automatically change bakery baking parameters like temperature and humidity. It also features energy efficient, cyber secure, and customer feedback products. The results of the experiment showed improved product consistency, low energy consumption and higher customer satisfaction, revealing a possibility of the scalability of the system in sustainable food-supply chains [144]. Yet another student-developed project in India also provided an IoT-based system to monitor food safety using ESP32 microcontrollers, sensors and a camera module. This was a system that connected data with cloud dashboard and Telegram bot to enable real-time monitoring and notifications. The system was affordable, scalable and easy to deploy at different points in the food supply chain (such as in storage, transportation or retail) [145,146].

11. Conclusion and Future Research Roadmap

The integration of cutting-edge artificial intelligence technologies such as Deep Learning, Reinforcement Learning, and Explainable AI, is having a profound impact on food systems. The technologies support the transition from traditional agriculture with high resource and energy consumption to predictive, adaptive and regenerative farming. AI underpins the analytics needed to enhance productivity, sustainability, minimize waste, and enable the emergence of new protein and food platforms. The linkage of basic AI research with on-farm practices also helps to improve the outcomes of intelligent systems throughout the full value chain of food production, processing, distribution and nutrition (molecular plant breeding, crop production, processing, supply chain and nutrition). As a result, such AI powered food systems hold great potential to improve efficiency, robustness, and sustainability, and are beneficial for global food security. But there are several research and systemic barriers. There is a clear need for future research to focus on reasoning and system level integration of AI technologies to include sustainability objectives, ethical considerations and human health in sustainable food systems. Progress from yield-centric to ecological and societal goals in food production is critical. Concurrently, digital discovery platforms and autonomous laboratories should be explored as potential, new pathway developments for turning food into a programmable biomaterial, driving innovation for novel ingredients and functional and sustainable protein product development. Additionally, in a changing climate, robust and adaptive AI approaches are required. Distributed learning techniques such as federated learning and knowledge transfer based on large language models can improve model resilience, while enabling adaptable food systems for climate change and extreme weather events.

The future of AI driven agriculture also requires collaboration across disciplines to integrate technology, policy, and society. Adaptation strategies for different regions need to match AI technologies to local agricultural needs, and ensure digital empowerment. Successful deployment ensures robust governance models, capacity building programs and inclusive data ecosystems. Collaboration between government agencies, research institutions, technology providers, and agricultural stakeholders is crucial to drive long-term sustainable deployment and create maximum impact. Further, integrating AI with other technologies such as biotechnology, nanotechnology and blockchain opens new possibilities. AI-assisted biotechnology helps create nutritionally fortified and ecofriendly food products, with nanotechnology enabling targeted nutrient and longer food shelf life. Likewise, combining blockchain and AI improves food traceability, and enables transparency of the food supply chain, logistics cost reduction, and better food safety. But ethical, technical and socio-economic barriers still stand in the way of widespread adoption of AI in agriculture. The upfront capital costs for smart farming systems, such as sensors, robotics, and machine learning systems make it difficult for small and medium sized farms and emerging markets to adopt AI technologies. Further, AI agriculture depends on large scale data collection and analyses, but poor internet infrastructure, lack of computing power and power supply in rural areas limit the adoption of AI technologies. Data management also questions issues surrounding data ownership, privacy and share of the value. Trading agricultural data to large technology companies poses challenges of farmer autonomy and control over agricultural knowledge systems. And automation may displace traditional forms of agricultural work, leading to reskilling and information technology literacy programs.

Fairness and bias of algorithms is another issue. AI algorithms trained on past agricultural practices may skew towards industrialized monoculture at the expense of smallholder and ecosystems diversity. This can have implications on environmental and social sustainability. Sustainable and equitable food systems can be promoted through transparent, explainable and inclusive AI systems that enable fair decision making and safeguard food sovereignty. Multilateral governance, open data and participatory AI design can play a pivotal role in promoting equitable use of AI in agriculture.

In sum, AI based sustainable food systems are a paradigm shift towards productivity, environmental sustainability and socio-economic resilience. The successful implementation of this vision relies on the development of interpretable and adaptive AI models, infrastructure development, fair data governance and cross-disciplinary collaboration. By investing in research, policy and human capital development, AI can emerge as an integral technology for sustainable feeding of the world without undermining the environment. The question is no longer if, but at what speed and with what fairness AI systems can be embraced to enable inclusive, sustainable and resilient agricultural innovation.

Acknowledgements

Thanks to the University of Mosul.

Authors’ Contribution

All authors played an equal role in the development, design, execution, analysis and production of the manuscript. All authors have read and approved the manuscript. Dr. Luma Alharbawee is corresponding author.

Ethics information

This study did not involve human participants or animal subjects, and therefore ethical approval was not required.

Funding

No funds.

Conflicts of interest

The authors declare that they have no competing interests.

References

[1] A. Sharma, L. Chen, and M. Patel, “Fourier-Bessel integrals in high-dimensional data analysis and neural signal processing,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 47, no. 3, pp. 485–498, Mar. 2025.

[2] Z. Namkhah, S. F. Fatemi, A. Mansoori, S. Nosratabadi, M. Ghayour-Mobarhan, and S. R. Sobhani, “Advancing sustainability in the food and nutrition system: a review of artificial intelligence applications,” in *Frontiers in Nutrition*, vol. 10, 2023, p. 1295241.

[3] A. A. Mana, A. Allouhi, A. Hamrani, S. Rehman, I. El Jamaoui, and K. Jayachandran, “Sustainable AI-based production agriculture: Exploring AI applications and implications in agricultural practices,” in *Smart Agricultural Technology*, vol. 7, 2024, p. 100416.

[4] E. E. K. Senoo, L. Anggraini, J. A. Kumi, L. B. Karolina, E. Akansah, H. A. Sulyman, and M. Aritsugi, “IoT solutions with artificial intelligence technologies for precision agriculture: definitions, applications, challenges, and opportunities,” in *Electronics*, vol. 13, no. 10, 2024, p. 1894.

[5] A. Di Vaio, F. Boccia, L. Landriani, and R. Palladino, “Artificial intelligence in the agri-food system: rethinking sustainable business models in the COVID-19 scenario,” *Sustainability*, vol. 12, no. 12, 2020, p. 4851.

[6] G. D’Amore, A. Di Vaio, D. Balsalobre-Lorente, and F. Boccia, “Artificial intelligence in the water–energy–food model: a holistic approach towards sustainable development goals,” *Sustainability*, vol. 14, no. 2, 2022, p. 867.

[7] S. B. Dhal and D. Kar, “Transforming agricultural productivity with AI-driven forecasting: Innovations in food security and supply chain optimization,” in *Forecasting*, vol. 6, no. 4, 2024, pp. 925–951.

[8] N. Aijaz, H. Lan, T. Raza, M. Yaqub, R. Iqbal, and M. S. Pathan, “Artificial intelligence in agriculture: Advancing crop productivity and sustainability,” in *Journal of Agriculture and Food Research*, 2025, p. 101762.

[9] F. Assimakopoulos, C. Vassilakis, D. Margaris, K. Kotis, and D. Spiliotopoulos, “Artificial intelligence tools for the agriculture value chain: Status and prospects,” in *Electronics*, vol. 13, no. 22, 2024, p. 4362.

[10] F. Assimakopoulos, C. Vassilakis, D. Margaris, K. Kotis, and D. Spiliotopoulos, “AI and related technologies in the fields of smart agriculture: A review,” in *Information*, vol. 16, no. 2, 2025, p. 100.

[11] M. Z. Ahmed, Advanced Electromagnetic Theory for AI Applications, 4th ed., vol. 2. Cambridge, MA: MIT Press, 2025, pp. 102–115.

[12] L. Alharbawee, S. Altaee, A. Alyoons, and N. Pugeault, “Advanced machine learning techniques and GIS for population census prediction,” in Proc. 2025 3rd Int. Conf. Business Analytics for Technology and Security (ICBATS), May 2025, pp. 1–8.

[13] H. Balcıoğlu, M. B. Durmuşoğlu, and G. Akçapınar, “Ethical and technical challenges in AI-driven food systems: A review,” in *J. Clean. Prod.*, vol. 445, 2024, p. 140857.

[14] H. B. Jadhav, K. Alaskar, V. Desai, A. Sane, P. Choudhary, U. Annapure, J. Uddin, and G. A. Nayik, “Transformative impact: Artificial intelligence in the evolving landscape of processed food—A concise review focusing on some food processing sectors,” in *Food Control*, vol. 167, 2025, p. 110803.

[15] T. Nguyen and R. Dasgupta, “Sparse representations and anisotropic filtering in computer vision,” in Advances in Computational Mathematics, vol. 9, Y. Zhao and H. Lin, Eds. New York, NY: Springer, 2025, pp. 233–264.

[16] Y. Ding, T. Zhang, and H. Li, “Artificial intelligence for sustainable food production: A bibliometric and trend analysis,” in *J. Environ. Manage.*, vol. 341, 2023, p. 117061.

[17] V. Zatsu, A. E. Shine, J. M. Tharakan, D. Peter, T. V. Ranganathan, S. S. Alotaibi, … and G. A. Nayik, “Revolutionizing the food industry: The transformative power of artificial intelligence—a review,” in *Food Chemistry: X*, vol. 24, 2024, p. 101867.

[18] K. Bandyopadhyay, S. Ghosh, and R. K. Gope, “Application of artificial intelligence in food industry—a review,” in *International Journal of Engineering Applied Sciences and Technology*, vol. 5, no. 11, 2021, pp. 145–152.

[19] Y. Lin, J. Ma, Q. Wang, and D.-W. Sun, “Applications of machine learning techniques for enhancing nondestructive food quality and safety detection,” *Critical Reviews in Food Science and Nutrition*, vol. 63, no. 12, pp. 1649–1669, 2023.

[20] S. B. Dhal and D. Kar, “Leveraging artificial intelligence and advanced food processing techniques for enhanced food safety, quality, and security: A comprehensive review,” in *Discover Applied Sciences*, vol. 7, no. 1, 2025, pp. 1–46.

[21] M. D. P. Ta, S. Wendt, and T. O. Sigurjonsson, “Applying artificial intelligence to promote sustainability,” *Sustainability*, vol. 16, no. 12, 2024, p. 4879.

[22] A. Taneja, G. Nair, M. Joshi, S. Sharma, S. Sharma, A. R. Jambrak, E. Roselló-Soto, *et al.*, “Artificial intelligence: implications for the agri-food sector,” *Agronomy*, vol. 13, no. 5, 2023, p. 1397.

[23] S. Bendre, K. Shinde, N. Kale, and S. Gilda, “Artificial intelligence in food industry: A current panorama,” in *Asian Journal of Pharmacy and Technology*, vol. 12, no. 3, 2022, pp. 242–250.

[24] T. Chen, L. Lv, D. Wang, J. Zhang, Y. Yang, Z. Zhao, … and D. Tao, “Empowering agrifood system with artificial intelligence: A survey of the progress, challenges and opportunities,” in *ACM Computing Surveys*, vol. 57, no. 2, 2024, pp. 1–37.

[25] K. Agrawal, P. Goktas, M. Holtkemper, C. Beecks, and N. Kumar, “AI-driven transformation in food manufacturing: A pathway to sustainable efficiency and quality assurance,” in *Frontiers in Nutrition*, vol. 12, 2025, p. 1553942.

[26] J. R. Owens, “Novel cryptographic schemes for post-quantum systems,” unpublished manuscript, University of California, Berkeley, 2025. [5] K. Torres, “Deep learning architectures for high-accuracy medical image segmentation,” J. Comput. Intell. Syst., in press, 2025.

[27] K. Torres, “Deep learning architectures for high-accuracy medical image segmentation,” J. Comput. Intell. Syst., in press, 2025.

[28] A. García de Vinuesa, E. Demir, and R. Myrzakulov, “ADAPTS: A data-driven framework for sustainability assessment in engineering systems,” in *Sustain. Cities Soc.*, vol. 56, 2020, p. 102105.

[29] K. B. Chhetri, “Applications of artificial intelligence and machine learning in food quality control and safety assessment,” in *Food Engineering Reviews*, vol. 16, no. 1, 2024, pp. 1–21.

[30] S. L. Li, D. Du, J. Wang, and Z. Wei, "Application progress of intelligent flavor sensing system in the production process of fermented foods based on the flavor properties," Crit. Rev. Food Sci. Nutr., pp. 1–30, 2022, doi: 10.1080/10408398.2022.2134982.

[31] Alduweib, E., Alromema, W., & Hezzam, E. (2025, April). Artificial Intelligence for Green Agriculture and Sustainable Resource Management: A Comprehensive Overview. In *2025 1st International Conference on Computational Intelligence Approaches and Applications (ICCIAA)* (pp. 1-5). IEEE.

[32] B. Thibault, M. Zeynoddin, H. Bonakdari, C. Ratti, and S. Khalloufi, "Predicting porosity of dehydrated food products using AI," in *Computers and Electronics in Agriculture*, vol. 221, 2024, p. 108934.

[33] D. B. Lobell and S. M. Gourdji, "The influence of climate change on global crop productivity," in *Plant Physiology*, vol. 160, no. 4, 2012, pp. 1686–1697.

[34] D. Mengistu and G. Ashe, "Review on Artificial Intelligence Powered Food Processing: Enhancing Safety and Sustainability," in *Asian Science Bulletin*, vol. 3, no. 1, 2025, pp. 92–101.

[35] X. Song, X. Zhang, G. Dong, H. Ding, X. Cui, Y. Han, H. Huang, and L. Wang, "AI in food industry automation: applications and challenges," *Frontiers in Sustainable Food Systems*, vol. 9, p. 1575430, 2025.

[36] V. Sachithra and L. D. C. S. Subhashini, "How artificial intelligence uses to achieve agriculture sustainability: Systematic review," in *Artificial Intelligence in Agriculture*, vol. 8, 2023, pp. 46–59.

[37] Y. Wang, "Application of Artificial Intelligence in Food Industry: A Review," in *Agricultural Science and Food Processing*, vol. 2, no. 2, 2025, pp. 68–88.

[38] L. Zhu, P. Spachos, E. Pensini, and K. N. Plataniotis, "Deep learning and machine vision for food processing: A survey," in *Current Research in Food Science*, vol. 4, 2021, pp. 233–249.

[39] P. Roy, D. Kumar, and K. Kumar, "Harnessing AI and emerging technologies for sustainable food systems: innovations in automation and intelligent production," *Asian Journal of Research in Computer Science*, vol. 18, no. 4, pp. 115–135, 2025.

[40] S. Harikrishnan, D. Kaushik, P. Rasane, A. Kumar, N. Kaur, C. K. Reddy, … M. Kumar, "Artificial Intelligence in Sustainable Food Design: Technological, Ethical Consideration, and Future," in Trends in Food Science & Technology, 2025, p. 105152.

[41] S. Murugavalli, and R. Gopi, "Plant leaf disease detection using vision transformers for precision agriculture," in Scientific Reports, vol. 15, 2025, p. 22361.

[42] S. Mehdipour, S. A. Mirroshandel, and S. A. Tabatabaei, "Vision transformers in precision agriculture: a comprehensive survey," in *arXiv preprint*, arXiv:2504.21706, 2025.

[43] H. J. Marvin, Y. Bouzembrak, H. J. Van der Fels-Klerx, C. Kempenaar, R. Veerkamp, A. Chauhan, … B. Tekinerdogan, "Digitalisation and artificial intelligence for sustainable food systems," in Trends in Food Science & Technology, vol. 120, 2022, pp. 344–348.

[44] R. Choudhary, S. P. Mantri, M. V. A. Barse, and S. Chitnis, "Leveraging AI in smart agro-informatics: a review of data science applications," in International Research Journal on Advanced Engineering and Management (IRJAEM), vol. 2, no. 06, 2024, pp. 1964–1975.

[45] A. H. A. Hussein, K. A. Jabbar, A. Mohammed, and L. Jasim, "Harvesting the future: AI and IoT in agriculture," in E3S Web of Conferences, vol. 477, 2024, p. 00090.

[46] H. Ding, J. Tian, W. Yu, D. I. Wilson, B. R. Young, X. Cui, … W. Li, "The application of artificial intelligence and big data in the food industry," in Foods, vol. 12, no. 24, 2023, p. 4511.

[47] M. Gupta, M. Abdelsalam, S. Khorsandroo, and S. Mittal, "Security and privacy in smart farming: Challenges and opportunities," in IEEE Access, vol. 8, 2020, pp. 34564–34584.

[48] N. Sharma, S. Rout, B. Saritha, and S. K. Gautam, "A comprehensive review on future of smart farming and its role in shaping food production," in *Journal of Experimental Agriculture International*, vol. 46, no. 5, 2024, pp. 486–493.

[49] R. Ben Ayed, and M. Hanana, "Artificial intelligence to improve the food and agriculture sector," in Journal of Food Quality, vol. 2021, no. 1, 2021, p. 5584754.

[50] K. Shilpa, "Frontiers of artificial intelligence in agricultural sector: trends and transformations," in *Journal of Scientific Research and Reports*, vol. 30, no. 10, 2024, pp. 970–980.

[51] Wang, X., Wu, Q., Zeng, H., Yang, X., Cui, H., Yi, X., ... & Que, Y. (2025). Blockchain-Empowered H-CPS Architecture for Smart Agriculture. Advanced Science, 2503102.

[52] M. A. Alkhafaji, G. M. Ramadan, Z. Jaffer, and L. Jasim, "Revolutionizing agriculture: the impact of AI and IoT," in *E3S Web of Conferences*, vol. 491, 2024, p. 01010.

[53] K. S. Somashekar, H. M. Rehaman, G. S. Kumar, K. Bai, N. Belagalla, G. J. Abhishek, … M. Kapoor, “Technology for a food-secure future: a review of technology advances in sustainable agriculture,” in *Journal of Experimental Agriculture International*, vol. 46, no. 9, 2024, pp. 234–256.

[54] L. Schaefer, “An emerging era of artificial intelligence research in agriculture,” in *Journal of Robotics Spectrum*, vol. 1, 2023, pp. 036–046.

[55] P. Gupta, “Precision agriculture application using machine learning,” *International Journal of Advanced Research in Science, Communication and Technology*, 2023, pp. 1–8.

[56] V. Sánchez Castillo, “Analysis of the scientific production on the implementation of artificial intelligence in precision agriculture,” *LatIA*, vol. 1, 2023, p. 1.

[57] G. San Miguel, P. Núñez-Cárdenas, J. M. De la Rosa, B. Diezma, J. del Cerro, and E. C. Correa Hernando, “Techno-economic, environmental and social assessment of precision agriculture for stone fruit production,” in *18th International Conference on Environmental Science and Technology*, 2023.

[58] A. Lishchuk, A. Parfeniuk, N. Karachinska, and I. Beznosko, “Innovations of precision agriculture in reducing environmental risks in agroecosystems of Ukraine,” *Balanced Nature Using*, vol. 3, 2024, pp. 105–113.

[59] R. L. Patibandla, B. T. Rao, and R. M. Malla, “Precision agriculture and AI: Nurturing sustainable food ecosystems,” in *AI in Agriculture for Sustainable and Economic Management*, CRC Press, 2024, pp. 78–91.

[60] M. Padhiary, A. Hoque, G. Prasad, K. Kumar, and B. Sahu, “Precision agriculture and AI-driven resource optimization for sustainable land and resource management,” in *Smart Water Technology for Sustainable Management in Modern Cities*, J. Ruiz-Vanoye and O. Díaz-Parra, Eds., IGI Global Scientific Publishing, 2025, pp. 197–232.

[61] M. Corrêa da Silva and C. F. Ruviaro, “Environmental gains of precision agriculture in Brazilian soybean production: A life cycle assessment approach,” *Archives of Current Research International*, vol. 25, no. 8, pp. 163–177, 2025, doi: 10.9734/acri/2025/v25i81405.

[62] H. V. Rani, P. Kakkar, and D. P. Singh, “Advancements in precision agriculture for maximizing crop yield and minimizing waste via innovative technological solutions,” *International Journal of Research and Review in Applied Science, Humanities, and Technology*, vol. 2, no. 1, 2025, pp. 1–8.

[63] B. G. Anicet, A. D. Vibhute, I. Aitouhanni, Y. Mouniane, I. El-Khadir, A. Chriqui, S. Mehdioui, and D. Hmouni, “Precision agriculture and artificial intelligence: Towards sustainable resource management in the face of climate challenges,” in *Generative Adversarial Networks for Remote Sensing*, A. Vibhute, R. Dhanaraj, and K. Kale, Eds., IGI Global Scientific Publishing, 2025, pp. 227–256.

[64] M. Balasubramani, M. P. Rajakumar, R. Suganthi, M. Navaneetha Krishnan, K. Raghavi, and M. Robinson Joel, “Using AI to improve crop tracking, soil investigation, and nutrient management in precision agriculture,” in *Precision and Intelligence in Agriculture: Advanced Technologies for Sustainable Farming*, P. Whig and A. Elngar, Eds., IGI Global Scientific Publishing, 2026, pp. 247–272.

[65] E. Lazarou, S. Bitsika, and S. Fountas, “Smart droplets: Accelerating the achievement of EU Green Deal goals for pesticide and fertilizer reduction,” in *2025 6th International Conference in Electronic Engineering & Information Technology (EEITE)*, Chania, Greece, 2025, pp. 1–11.

[66] H. Alibašić, “Digitalisation and artificial intelligence for sustainable food systems,” *Trends in Food Science & Technology*, vol. 120, pp. 344–348, 2022, doi: 10.1016/j.tifs.2022.01.020.

[67] S. C. Sakapaji and J. J. Puthenkalam, “Harnessing AI for climate-resilient agriculture: Opportunities and challenges,” *European Journal of Theoretical and Applied Sciences*, vol. 1, no. 6, pp. 1144–1158, 2023, doi: 10.59324/ejtas.2023.1(6).111.

[68] R. Khadka and V. Kumar, “Enhancing sustainability in agriculture through artificial intelligence,” in International Scientific Journal of Engineering Management, vol. 3, no. 12, 2024, pp. 1–7.

[69] O. Olasehinde, B. K. Alese, and O. Eqwuche, “Privacy-preserving artificial intelligence: Principles, methods, applications, and challenges,” Journal of Applied Artificial Intelligence, vol. 6, no. 2, pp. 60–70, 2025.

[70] O. B. Akintuyi, “The role of artificial intelligence in US agriculture: a review: assessing advancements, challenges, and the potential impact on food production and sustainability,” in *Open Access Research Journal of Engineering and Technology*, vol. 6, no. 02, 2024, pp. 23–32.

[71] N. Boora and N. Ahalawat, “The transformative role of AI in agriculture: revolutionizing farming practices and sustainability,” in *Futuristic Trends in Renewable & Sustainable Energy*, vol. 3, book 5, IIP Series, May 2024, pp. 1–18, e-ISBN: 978-93-6252-460-7

[72] N. Boora and N. Ahalawat, “The transformative role of AI in agriculture: revolutionizing farming practices and sustainability,” in *Futuristic Trends in Renewable & Sustainable Energy*, vol. 3, book 5, IIP Series, May 2024, pp. 1–18, e-ISBN: 978-93-6252-460-7

[73] R. I. Almoselhy and A. Usmani, “AI in food science: exploring core elements, challenges, and future directions,” in *Open Access Journal of Microbiology and Biotechnology*, vol. 9, no. 4, 2024, pp. 1–15.

[74] M. Marković, A. Li, T. A. Ayall, N. J. Watson, A. L. Bowler, M. Woods, *et al.*, “Embedding AI-enabled data infrastructures for sustainability in agri-food: soft-fruit and brewery use case perspectives,” in *Sensors*, vol. 24, no. 22, 2024, p. 7327.

[75] R. B. Abdallah, H. B. Aribi, E. B. Amara, I. Othmeni, and S. Fattouch, “Artificial intelligence for sustainable food systems,” in *Fostering Cross-Industry Sustainability with Intelligent Technologies*, IGI Global Scientific Publishing, 2024, pp. 457–477.

[76] A. Joshi, “Harnessing artificial intelligence for sustainable food production,” in *AI Innovations for Transforming Food Production*, IGI Global Scientific Publishing, 2026, pp. 25–56.

[77] M. I. Keskes, “Artificial intelligence in precision fruit agriculture: Sustainability, innovations, and outlook,” *OSF Preprints*, 2025, doi: 10.31219/osf.io/emz58_v1.

[78] T. Miller, G. Mikiciuk, I. Durlik, M. Mikiciuk, A. Łobodzińska, and M. Śnieg, “The IoT and AI in agriculture: The time is now—A systematic review of smart sensing technologies,” *Sensors*, vol. 25, no. 12, Art. no. 3583, 2025.

[79] Alharbawee, L., & Pugeault, N. (2021). A benchmark of dynamic versus static methods for facial action unit detection. The Journal of Engineering, 2021(5), 252-266.

[80] Z. Ali, A. Muhammad, N. Lee, M. Waqar, and S. W. Lee, “Artificial intelligence for sustainable agriculture: A comprehensive review of AI-driven technologies in crop production,” *Sustainability*, vol. 17, no. 5, Art. no. 2281, 2025.

[81] X. Wang, F. Meng, X. Liu, Z. Kong, and X. Chen, “Causal explanation for reinforcement learning: Quantifying state and temporal importance,” *arXiv preprint*, arXiv:2210.13507, 2022.

[82] I. Tagkopoulos, S. F. Brown, X. Liu, Q. Zhao, T. I. Zohdi, J. M. Earles, *et al*., “Special report: AI Institute for next generation food systems (AIFS),” *Computers and Electronics in Agriculture*, vol. 196, Art. no. 106819, 2022.

[83] N. Rane, S. P. Choudhary, and J. Rane, “Acceptance of artificial intelligence: Key factors, challenges, and implementation strategies,” Journal of Applied Artificial Intelligence, vol. 5, no. 2, pp. 50–70, 2024.

[84] McKinsey & Company, “How AI can unlock a $127B opportunity by reducing food waste,” *McKinsey Sustainability Blog*, 2025. [Online]. Available: https://www.mckinsey.com/capabilities/sustainability/our-insights/sustainability-blog/how-ai-can-unlock-a-127b-opportunity-by-reducing-food-waste. Accessed: Dec. 10, 2025.

[85] R. J. Mohan, P. S. Rayanoothala, and R. P. Sree, “Next-gen agriculture: Integrating AI and XAI for precision crop yield predictions,” *Frontiers in Plant Science*, vol. 15, Art. no. 1451607, 2025.

[86] J. Yu, Q. Qu, S. Peng, X. Wei, Y. Li, and C. Sun, “Deep learning for intelligent irrigation decision-making: A review,” *Agricultural Water Management*, vol. 320, Art. no. 109836, 2025.

[87] Frost & Sullivan, “The robotics revolution in agri-food: How AI and automation are transforing the future of sustainable food systems,” *Growth Opportunity News*, 2025. [Online]. Available: https://www.frost.com/growth-opportunity-news/industrial/electronics-measurement/the-robotics-revolution-in-agri-food-how-ai-and-automation-are-transforming-the-future. Accessed: Dec. 10, 2025.

[88] G. Mengistu and G. Ashe, “Review of artificial intelligence powered food processing: Enhancing safety and sustainability,” *Journal of Agroalimentary Processes & Technologies*, vol. 30, no. 2, 2024.

[89] Alharbawee, L., & Pugeault, N. (2024). Generative adversarial networks for facial expression recognition in the wild. International Journal of Computing and Digital Systems, 16(1), 1259-1282.

[90] Z. Liu, S. Wang, Y. Zhang, Y. Feng, J. Liu, and H. Zhu, “Artificial intelligence in food safety: A decade review and bibliometric analysis,” *Foods*, vol. 12, no. 6, Art. no. 1242, 2023.

[91] BCC Research, “How AI is transforming food safety & quality control in 2025,” *BCC Research Blog*, 2025. [Online]. Available: https://blog.bccresearch.com/how-ai-is-transforming-food-safety-quality-control-in-2026. Accessed: Dec. 10, 2025.

[92] H. Onyeaka, P. Tamasiga, U. M. Nwauzoma, T. Miri, U. C. Juliet, O. Nwaiwu, and A. A. Akinsemolu, “Using artificial intelligence to tackle food waste and enhance the circular economy: Maximising resource efficiency and minimising environmental impact: A review,” *Sustainability*, vol. 15, no. 13, Art. no. 10482, 2023.

[93] B. Datta, M. J. Buehler, Y. Chow, K. Gligorić, D. Jurafsky, D. L. Kaplan, *et al*., “AI for sustainable future foods,” *arXiv preprint*, arXiv:2509.21556, 2025.

[94] S. Çakmakçı, B. Polatoğlu, and R. Çakmakçı, “Foods of the future: Challenges, opportunities, trends, and expectations,” *Foods*, vol. 13, no. 17, Art. no. 2663, 2024.

[95] M. Nautiyal, S. Joshi, I. Hussain, H. Rawat, A. Joshi, A. Saini, *et al*., “Revolutionizing agriculture: A comprehensive review on artificial intelligence applications in enhancing properties of agricultural produce,” *Food Chemistry: X*, Art. no. 102748, 2025.

[96] I. Dawar, S. Negi, and A. Chauhan, “Explainable AI for next generation agriculture—Current scenario and future prospects,” in *Computational Intelligence in Internet of Agricultural Things*, Cham, Switzerland: Springer Nature, 2024, pp. 171–192.

[97] A. Rabadán, R. Nieto, and R. Bernabéu, "Food innovation as a means of developing healthier and more sustainable foods," Foods, vol. 10, no. 9, Art. no. 2069, 2021, doi: 10.3390/foods10092069.

[98] D. J. McClements, R. Barrangou, C. Hill, J. L. Kokini, M. A. Lila, A. S. Meyer, and L. Yu, "Building a resilient, sustainable, and healthier food supply through innovation and technology," Annu. Rev. Food Sci. Technol., vol. 12, no. 1, pp. 1–28, 2021, doi: 10.1146/annurev-food-092220-030824.

[99] C. A. M. Anderson, A. N. Thorndike, A. H. Lichtenstein, L. Van Horn, P. M. Kris-Etherton, R. E. Foraker, and C. Spees, "Innovation to create a healthy and sustainable food system: A science advisory from the American Heart Association," Circulation, vol. 139, no. 23, 2019, doi: 10.1161/cir.0000000000000686.

[100] A. Phalle and D. Gokhale, "Navigating next-gen nutrition care using artificial intelligence-assisted dietary assessment tools—a scoping review of potential applications," Front. Nutr., vol. 12, 2025, doi: 10.3389/fnut.2025.1518466.

[101] D. M. Thomas, R. Knight, J. A. Gilbert, M. C. Cornelis, M. G. Gantz, K. Burdekin, K. Cummiskey, S. C. J. Sumner, W. Pathmasiri, E. Sazonov, K. P. Gabriel, E. E. Dooley, M. A. Green, A. Pfluger, and S. Kleinberg, "Transforming big data into AI-ready data for nutrition and obesity research," Obesity, 2024, doi: 10.1002/oby.23989.

[102] K. Karnika, S. Sharma, A. Singh, S. S. Batth, and A. Sharma, "From data to diet: The impact of artificial intelligence on nutritional science," J. Sci. Res. Rep., vol. 31, no. 8, pp. 449–458, 2025, doi: 10.9734/jsrr/2025/v31i83388.

[103] S. Zhang, C. Lai, J. Zhao, and J. Wang, "Big data and AI-powered modeling: A pathway to sustainable precision animal nutrition," Adv. Sci., 2025, doi: 10.1002/advs.202507564.

[104] H. Kassem, A. S. Beevi, S. Basheer, G. Lutfi, L. C. Ismail, and D. Papandreou, "Investigation and assessment of AI’s role in nutrition—An updated narrative review of the evidence," Nutrients, vol. 17, no. 1, Art. no. 190, 2025, doi: 10.3390/nu17010190.

[105] B. S. Bahnam and S. A. Dawwod, "A proposed model for diabetes mellitus classification using coyote optimization algorithm and least squares support vector machine," IAES Int. J. Artif. Intell. (IJ-AI), vol. 11, no. 3, pp. 1164–1174, Sep. 2022, doi: 10.11591/ijai. v11.i3.

[106] M. Capocasa and D. Venier, "Artificial intelligence in nutrition science: Balancing innovation and ethical responsibility," Nutr. Health, 2025, doi: 10.1177/02601060251375834.

[107] K. J. Mendoza-Bautista, M. S. Flores-Jiménez, L. Serrano, G. Trujillo-de Santiago, M. M. Álvarez, A. Molina, M. Alfaro-Ponce, and I. Chaírez, “Collaborative heterogeneous mini-robotic 3D printer for manufacturing complex food structures with multiple inks and curved deposition surfaces,” Micromachines, vol. 16, no. 3, Art. no. 264, 2025, doi: 10.3390/mi16030264.

[108] Y. Phimolsiripol and B. Grau, “Innovations and applications of 3-D printing in food sector,” Int. J. Food Sci. Technol., vol. 57, no. 6, pp. 3326–3332, 2022, doi: 10.1111/ijfs.15691.

[109] A. Schiffer, N. Sahai, and S. Ratnavel, “3D printing technologies and automation in food processing industry: An innovative marketing approach for health and digital gastronomy perspective,” ChemRxiv, 2024, doi: 10.26434/chemrxiv-2024-q37xr.

[110] M. Padhiary, J. A. Barbhuiya, D. Roy, and P. Roy, “3D printing applications in smart farming and food processing,” Applied Technology, 2024, doi: 10.1016/j.atech.2024.100553.

[111] S. L. Li, D. Du, J. Wang, and Z. Wei, "Application progress of intelligent flavor sensing system in the production process of fermented foods based on the flavor properties," Crit. Rev. Food Sci. Nutr., pp. 1–30, 2022, doi: 10.1080/10408398.2022.2134982.

[112] P. Krishnan, U. S. Ebenezar, R. Ranitha, N. Purushotham, and T. S. Balakrishnan, "AI-driven intelligent IoT systems for real-time food quality monitoring and analysis," IEEE Trans. Quant. Eng. Biotechnol., vol. 29, pp. 1–5, 2024, doi: 10.1109/tqcebt59414.2024.10545305.

[113] L. B. Ebenezer, S. Anbalagan, and C. Baskar, "Advances in bioinspired sensing—electronic nose and eye technologies for food quality assessment: A review," IEEE Sensors J., 2025, doi: 10.1109/jsen.2025.3590474.

[114] E. Henrichs and C. Krupitzer, "Towards a self-adaptive, real-time monitoring system for food quality assessment," pp. 178–179, 2024, doi: 10.1109/acsos-c63493.2024.00056.

[115] D. Wang, M. Zhang, Q. Jiang, and A. S. Mujumdar, "Intelligent system/equipment for quality deterioration detection of fresh food: Recent advances and application," Foods, vol. 13, no. 11, Art. no. 1662, 2024, doi: 10.3390/foods13111662.

[116] B. P. Dayananda and D. Cozzolino, "Beyond the black box—practical considerations on the use of chemometrics combined with sensing technologies in food science applications," Chemosensors, vol. 10, no. 8, Art. no. 323, 2022, doi: 10.3390/chemosensors10080323.

[117] M. Durgun, "Real-time milk quality control using multi-spectral sensing and edge computing: Advancing on-site detection of milk components with XGBoost," Appl. Sci., vol. 14, no. 23, Art. no. 10916, 2024, doi: 10.3390/app142310916.

[118] M. A. Nikitina and I. M. Chernukha, “Personalized nutrition and ‘digital twins’ of food,” vol. 14, pp. 264–270, 2020, doi: 10.5219/1312.

[119] J. Qiao, M. Zhang, L. Qiu, A. S. Mujumdar, and Y. Ma, “Visual early warning and prediction of fresh food quality deterioration: Research progress and application in supply chain,” Food Biosci., 2024, doi: 10.1016/j.fbio.2024.103671.

[120] C. Krupitzer, T. Noack, and C. Borsum, “Digital food twins combining data science and food science: System model, applications, and challenges,” Processes, vol. 10, no. 9, Art. no. 1781, 2022, doi: 10.3390/pr10091781.

[121] C. Krupitzer and T. Noack, “DigiFoodTwin: Digital biophysical twins combined with machine learning for optimizing food processing,” in Proc. European Conf. on Planning, 2022, doi: 10.3390/ecp2022-12623.

[122] C. Krupitzer and E. Henrichs, “Digitale Zwillinge in der Lebensmittelversorgung: Ein Überblick über das Potenzial und die Herausforderungen von Digitalen Zwillingen für die Lebensmittelversorgung,” Industrie 4.0 Manag., 2022, no. 5, pp. 17–20, doi: 10.30844/im_22-5_17-20.

[123] W. Y. Leong, Y. Z. Leong, and W. S. Leong, “Enhancing poultry farm operations with IoT and smart manufacturing systems,” in Proc. ICTKE, 2024, pp. 1–5, doi: 10.1109/ictke62841.2024.10787167.

[124] M. M. Rahman, E. A. Rana, N. N. Tamzi, I. Saha, and F. H. Siddiqui, “A deep learning approach-FDNN: Forest deep neural network to predict cow’s parturition date,” Journal of Applied Artificial Intelligence, vol. 3, no. 1, pp. 61–74, 2022.

[125] M. K. Bali and M. Singh, "Farming in the Digital Age: AI-Infused Digital Twins for Agriculture," 2024. doi: 10.1109/icsadl61749.2024.00009.

[126] M. Escribà-Gelonch, S. Liang, P. van Schalkwyk, I. Fisk, N. Van Duc Long, and V. Hessel, "Digital Twins in Agriculture: Orchestration and Applications," Journal of Agricultural and Food Chemistry, 2024. doi: 10.1021/acs.jafc.4c01934.

[127] D. Shamia, S. Suganyadevi, V. Satheeswaran, and K. Balasamy, "Digital twins in precision agriculture monitoring using artificial intelligence," in Elsevier BV, 2023, pp. 243–265. doi: 10.1016/b978-0-323-99205-3.00004-3.

[128] G. Costa, A. Forestiero, A. F. Gentile, D. Macrì, R. Ortale, B. Bernardi, and E. Cerruto, "An AI-Driven Architecture for Precision Agriculture: IoT, Machine Learning, and Digital Twin Integration for Sustainable Crop Protection," 2024, pp. 4685–4691. doi: 10.1109/bigdata62323.2024.10826124.

[129] B. Thakkar, S. R. Shaikh, P. Katkade, and V. A. Shukre, "Leveraging Artificial Intelligence, Internet of Things, and Digital Twins in Sustainable Agriculture," 2024, pp. 1–6. doi: 10.1109/sparc61891.2024.10829179.

[130] R. K. Sahni, M. Sharma, S. P. Kumar, D. Thorat, C. Yumnam, S. Soni, K. Kumari, A. Kumari, R. Yadav, S. Kumar, and M. K. Sinha, “Application of sensors and instrumentation in precision agriculture,” J. Sci. Res. Rep., vol. 31, no. 8, pp. 823–836, 2025, doi: 10.9734/jsrr/2025/v31i83425.

[131] A. Soussi, E. Zero, R. Sacile, D. Trinchero, and M. Fossa, "Smart Sensors and Smart Data for Precision Agriculture: A Review," Sensors, vol. 24, 2024. doi: 10.3390/s24082647.

[132] M. Ranwa, K. Sri, A. Khare, V. N. Kumar, K. Kumar, J. Rajeshwar, and M. Niharika, “A summative review of advances in sensor technology for precision agriculture,” Arch. Curr. Res. Int., vol. 24, no. 10, pp. 257–275, 2024, doi: 10.9734/acri/2024/v24i10929.

[133] M. C. Younis, Z. J. Fadil, and B. S. Bahnam, "IoT-based system for human localization activity recognition using hybrid deep learning techniques," Inteligencia Artif., vol. 28, no. 75, pp. 298–314, 2024, doi: 10.4114/intartif. vol28iss75pp298-314.

[134] S. Singaraju, S. N. K. G, J. R. D. B, N. P. S, and G. S. Shankar, "Enhancing Crop Yield Prediction: A Data-Driven Comparison of Regression Models in Agricultural Analytics," Proc. INCET, pp. 1–7, 2025. doi: 10.1109/incet64471.2025.11140851.

[135] N. A. Farooqui, M. A. Haleem, W. A. Khan, and M. Ishrat, "Precision Agriculture and Predictive Analytics," in Emerging Technologies in Agriculture (chapter 9), pp. 171–188, 2024. doi: 10.1002/9781394227990.ch9.

[136] V. Jain and A. Mitra, "Leveraging Machine Learning and Data Mining," in Advances in Computational Intelligence and Robotics, pp. 209–228, 2025. doi: 10.4018/979-8-3693-8161-8.ch011.

[137] Q. Zhang and M. Karkee, "Agricultural and Field Robotics: An Introduction," in Agricultural and Field Robotics, Springer, Cham, pp. 1–10, 2021. doi: 10.1007/978-3-030-70400-1_1.

[138] A. Amin, X. Wang, Y. Zhang, T. Li, Y. Chen, J. Zheng, Y. Shi, and M. A. Abdelhamid, "A Comprehensive Review of Applications of Robotics and Artificial Intelligence in Agricultural Operations," Studies in Informatics and Control, 2023. doi: 10.24846/v32i4y202306.

[139] P. Raj, V. Jayasankar, M. Agerstam, B. Sundaravadivazhagan, and R. Cyriac, "AI-Enabled Robots for Automating Oil and Gas Operations," 2023, pp. 177–198. doi: 10.1002/9781119985617.ch8.

[140] A. Y. Mulla and G. Ansurkar, "AI and robotics: Designing intelligent and adaptive robots for industrial automation," International Journal of Scientific Research in Science and Technology, 2023.

[141] S. Kakolu and M. Faheem, "Advanced robotics automation for field operations: Leveraging AI and machine learning for dynamic, real-world applications," International Journal of Science and Research Archive, vol. 11, no. 1, pp. 2605–2614, 2024. doi: 10.30574/ijsra.2024.11.1.0010.

[142] J. Xu et al., "Intelligent Dynamic Quality Prediction of Chilled Chicken with Integrated IoT Flexible Sensing and Knowledge Rules Extraction," Foods, vol. 11, no. 836, 2022.

[143] M. J. Islam, M. Alam, and M. A. H. Wadud, "Smart Food Monitoring System Based on IoT and Machine Learning," in Proc. 2023 International Conference on Next-Generation Computing, IoT and Machine Learning (NCIM), Bangladesh.

[144] A. Popa et al., "An Intelligent IoT-Based Food Quality Monitoring Approach Using Low-Cost Sensors," Symmetry, vol. 11, no. 374, 2019.

[145] I. Hussain, "Adaptive IoT and AI-Enhanced Quality Assurance System for Sustainable and Secure Bakery Production," International Journal of Innovative Science and Research Technology, vol. 9, no. 11, Nov. 2024.

C. A. R et al., "Ensuring Food Safety in the Digital Age: IoT Solutions for Food Quality Monitoring," International Journal for Multidisciplinary Research, vol. 5, no. 5, Sep.–Oct. 2023.