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Preface

Agriculture and food production systems face the common challenge of achieving all 17 sustainable development goals (SDGs). To achieve the SDGs, the Tsukuba Conference (TC) and Tsukuba Global Science Week (TGSW) organize global platforms to determine future policy challenges. This book is the outcome of our yearly efforts to address agricultural challenges, new developments to address climate change, and increased food production to meet global demands. Investing in the agricultural sector can address not only hunger and malnutrition but also other challenges, including poverty, water and energy use, climate change, and unsustainable production and consumption. To increase agricultural productivity, artificial intelligence (AI), machine learning (ML), and deep learning (DL) have led to the development of new prediction strategies for crop production, livestock development, and fisheries from pre-harvest to post-harvest levels. These digital innovations contribute to achieving the SDGs and Society 5.0.

In this book, Chap. 1 reviews the current digital innovations in agri-food systems and aligns them with their contributions toward achieving the SDGs and Society 5.0. Chapter 2 briefly describes current trends and digital innovations in mechanization and automation in smart agriculture. In Chap. 3, the authors present how farmers adopt strategies involving the use of agricultural machines such as combine harvesters for early harvests and the use of postproduction methods to counter fluctuations in crop production due to changing weather conditions. Chapter 4 further explains the appropriate agricultural mechanization scale for Southeast Asian countries. The various agricultural mechanization scales throughout the region and the current trends in agricultural mechanization and automation are also explained in this chapter.

Recent trends in automation include advanced sensors and actuators. The cost and availability of these technologies has made them more attractive for developing navigation platforms using light detection and ranging (LiDAR), global navigation satellite system (GNSS), and vision sensors. The application of sensors with the development of algorithms is described in this book. Some of the key problems and labor shortage areas are highlighted. Among them, the transportation of agricultural products from farms to consumers is particularly challenging. Therefore, Chap. 5 of this book discusses a small-scale navigation system of mobile robots to carry and deliver agricultural products using a combination of a Kalman filter, fuzzy control, and LiDAR techniques. Furthermore, Chap. 6 reviews the literature that has illustrated the potential of LiDAR for navigation systems in pesticide spraying vehicles in orchards. Since GPS and machine vision are easily influenced and limited by the environment, LiDAR was selected as the only sensor in this study, the planning paths were calculated via the density-based spatial clustering of applications with noise (DBSCAN), K-means, and random sample consensus (RANSAC) algorithms based on tree locations, and the vehicle was guided to follow the path. The feasibility of the system was proven by testing concrete roads and facilitated artificial-tree-based orchards.

With the aging of agricultural drivers worldwide, the safety risks associated with driving agricultural machinery have increased. Therefore, it is necessary to establish a stable, reliable, and effective system to ensure the safety of agricultural drivers. Thus, Chap. 7 elaborates on the application of AI to identify and classify drivers' actions while driving to determine dangerous behaviors and consequently provide an early warning signal to ensure driving safety. This research utilizes deep learning algorithms to determine dangerous driving behaviors to provide early warning signals to prevent accidents. Chapter 8 discusses the development of an autonomous agricultural vehicle based on stereo simultaneous localization and mapping (SLAM) for indoor environment usage. SLAMs are used to integrate the localization function with the construction of the surrounding environment. The environmental parameters that are important for vision SLAM are integrated with camera vision systems. Automation has advanced with the development of sensors ranging from infield plant production to inhouse production systems. Advancements in automations in agronomy are referred to as precision agronomics, which requires plant biophysical information in more detail. In this study, phenotyping plays a significant role in the prediction of growth and yield at the different stages of crop production cycles.

Plant phenotyping is an emerging science for quantifying and analyzing the characteristics of plants. The phenotyping process is particularly important for decision support in agriculture. Chapter 9 briefly describes how the advancement of plant phenotyping can be integrated with artificial intelligence to enhance crop quality resilience for food security under climate change. Chapter 10 is a short strategic note that highlights the application of artificial intelligence techniques in food quality detection. This chapter also discusses the gaps and future research directions that necessitate additional research attention to improve the current performance and applicability of AI-based food quality assessment. Chapter 11 emphasizes high-throughput plant phenotyping (HTPP), which focuses on indoor and controlled environments. Different sensors, techniques, and types of phenotyping are presented in this chapter to provide insight into the potential and development of non-destructive HTPP phenotyping.

In addition to phenotyping, early disease detection can also prevent disease outbreaks. Since plant crops tend to suffer severe impacts due to the fungus, yearlong pesticides are used to prevent foliar disease. However, these pesticides are concerning for human health and the environment. Furthermore, planting and horticultural crops need additional attention. In this regard, coffee is one of the most widely consumed beverages in the world, and its importance and economic value hold a significant position worldwide. Coffee production is threatened by a devastating disease called coffee leaf rust (*Hemileia vastatrix*), which is recognized as one of the major pests of coffee plantations worldwide. Chapter 12 discusses the need for and potential of modern pest management for coffee leaf rust and how deep learning could control this pest. Horticulture production faces several challenges affecting the yield and productivity of crops worldwide. Among these challenges are increasing labor and land costs, climate change, pest infestations, degrading soil nutrients, and water scarcity. To address these challenges, Chap. 13 discusses the digital transformation of horticultural crop production systems, highlighting the different digital technologies being implemented in pest, nutrient, canopy, and water management as well as in harvesting and post-harvest operations. Furthermore, this chapter also enumerated numerous challenges and opportunities for adopting the showcased digital technologies in horticultural production systems.

Another challenge for plantation crops is weed infestation. Common mechanical practices for weed removal are labor intensive, and new vision systems that use LiDAR and 3D cameras to navigate need to be developed. Chapter 14 describes the challenges of weed control using robotics in complex orchard environments. 3D cameras and LiDAR were subsequently introduced as solutions for navigation systems in orchard environments where the GNSS signal quality is poor due to tree canopy cover. Several advantages and drawbacks of both sensors are also explained. Finally, the chapter also provides examples of how both sensors are utilized in vehicles for weed control, especially for weeds located within rows; this approach is known to be quite difficult and tedious even though weeding is conducted by using a riding mower or by means of a hand grass cutter. The application of unmanned aerial vehicles (UAVs) in pesticide spraying plays an important role in precision agriculture. However, improvements in pesticide application efficiency and cost performance are still under discussion in this field. In Chap. 15, computational fluid dynamics were applied for simulations, and a variable spraying system (VSS) was developed to increase the efficiency of plant protection UAVs based on pulse width modulation reduction and spraying uniformity. In addition to the advancements in sensors and unmanned application development, another challenge is to address the global effects of climate change.

Climate change has a large geospatial dispersion, heterogenous effects across different environments, and unanticipated disturbances in weather and climatic variability. Therefore, climate smart adoption is highly important. Climate agricultural practices, including the adoption of certain crops and technologies, can provide long-term strategic support for agriculture worldwide. In this regard, Chap. 16 highlights the concept of climate smart agriculture (CSA) as an effort to mitigate the challenges of climate change in the agricultural sector. The CSA approach entails the establishment of technical, policy, and investment conditions to achieve sustainable agricultural development for food and nutrition security through climate-resilient and sustainable agriculture. Post-harvest operations are crucial for preserving agricultural product quality and shelf life. However, the complexity of post-harvest technology and the requirement for expertise in multiple domains make it difficult for companies to manage their operations efficiently. As a result, it is necessary to develop a central provider that provides expert scientific services to companies. Therefore, Chap. 17 briefly introduces the concept of the centralized data processing unit (CDPU) based on the integration of AI and data science to enhance post-harvest operations at the business level. The CDPU system can be integrated with the overall operational management of agricultural production from pre-harvest to post-harvest operations.

Irrigation plays a significant role in the operational management of agricultural fields. Smart water management is important for precise irrigation in agricultural fields as water becomes increasingly scarce. Hence, Chap. 18 explores the potential of smart water management through machine learning to understand plant root zones for irrigation purposes. Tuning the environmental parameters of conventional greenhouses, which need to be controlled manually by farmers, is inconvenient and imprecise. In Chap. 19, AI and IoT technology are presented as alternatives to farmer management of greenhouse systems to reduce the labor force and ensure that the conditions of the greenhouse environment (e.g., temperature, humidity, light intensity) more precisely correspond to the growth stages of lettuce plants. A new feedback control parameter was introduced using the Fuzzy proportional-integral-derivative (PID) controller, which significantly improved the accuracy of the optimization of the environmental control parameters of the greenhouse. Sensors and algorithms help controllers perform precise automated indoor cultivation of mushrooms, which are highly sensitive to weather parameters.

In Chap. 20, the author explores how AI and the IoT can be utilized to address various challenges in the artificial cultivation of mushrooms in tropical and subtropical regions. These technologies have the potential to enhance efficiency and minimize contamination throughout the entire process, from substrate preparation to harvesting. The practical applications discussed in this chapter offer valuable insights and can greatly benefit the local cottage mushroom industry. Furthermore, orchard applications are limited by the challenges of automation and harvesting due to labor shortages. Newly developed orchard architectures with genetic improvements create pathways for harvesting robots to reduce the complexity of the number of degrees of freedom, where complex robots are less adaptable in terms of economy and sustainability. The main challenges of harvesting robots include occlusions from leaves, branches, and fruit clusters for detection and localization. Chapter 21 provides an overview of the methods used to avoid occlusions to increase orchard fruit harvesting efficiency. In Chap. 22, various types of end-effectors commonly used in horticulture, including gripper end-effectors, cutting end-effectors, and spraying end-effectors, are discussed. Sensing and perception technologies, such as computer vision, LiDAR sensing, and thermal imaging, play a crucial role in end-effector automation by providing data about the environment and plants. Actuation and control mechanisms, including electric, pneumatic, and hydraulic technologies, allow for precise manipulation and adaptability of end-effectors. Deep learning algorithms have been applied to end-effector automation, enhancing tasks such as object classification, yield estimation, pest detection, and weed management. Case studies have demonstrated the design of a three-finger flexible gripper for orchard operations, offering a simple, cost-effective solution for fruit picking. Finally, we discuss the remaining challenges in developing smart automations for end-effectors.

Automations from pre-harvesting to post-harvest stages, including non-destructive quality assessment of foods, have become important criteria for the food industry. In the food industry automation, food quality analysis, imaging, and chemical analysis yield the highest quality assurance. Spectroscopy-based imaging is a non-destructive method that ensures a high-quality assessment of products. Chapter 23 elucidates the current advancements in spectroscopic techniques for food analysis. By exploring the advancements in spectroscopic techniques and their integration with chemometric tools, this chapter provides valuable insights into the potential applications and future directions of these analytical approaches in the food industry. Food diversification has become a food crisis intervention strategy supported by the FAO. Thus, Chap. 24 discusses the potential of endemic fruits to be adapted to local ecosystems.

Food and biomass production has received increased attention worldwide for achieving green energy and energy security. AI and IoT technologies can precisely forecast different stages of biomass production, which can be transformed to energy security to reduce the dependency on fossil fuel to mitigate GHG emissions. Chapter 25 discusses the implementation of the IoT in the agricultural sector, focusing on biomass residue utilization. Biomass residue has several potential applications, including for bioenergy generation. This study proposes the use of the IoT platform to measure the potential environmental impact of oil palm biomass residue for bioenergy. The platform was constructed based on the existing IoT platform on oil palm plantation management combined with a recently underdeveloped tool for calculating the potential impact of oil palm biomass residue utilization for ethanol, electricity generation, and fertilizer. It is expected that farmers, industrial sectors, fuel companies, users, and governments can benefit from the utilization of IoT systems to accelerate GHG mitigation in the future. Chapter 26 provides an integrated method for tracking and tracing agricultural productivity using a web-based IoT monitoring platform. The developed IoT systems visualize real-time environmental data, such as humidity, temperature, soil moisture content, wind speed, and rainfall parameters, acquired via the Dash platform. The insights gained from the system allow farm managers to monitor rainfall patterns and water cycles and make appropriate decisions or control remotely for optimal plant growth.

In addition to plant production, this book also highlights some of the research areas focusing on livestock and aquaculture. Recent advancements in sensors can help increase productivity. There are several IoT-based applications in aquaculture, which is one of the most important sources of animal protein worldwide. Aquaculture is the most economic approach and poses fewer risks as a major source of protein. Smart machine vision can be applied to reduce the need for manual observation in animal farming. Chapter 27 is a short note that demonstrates how smart machine vision can be applied to reduce the need for manual observation in both aquaculture and husbandry farming, which can contribute to strengthening food security. Chapter 28 introduces a novel, noninvasive method for assessing quail egg freshness using a thermal microcamera and deep learning algorithms. By analyzing thermal images and correlating the air cell area with egg weight, the models predicted freshness with high accuracy. This groundbreaking approach offers promising implications for the food industry and consumers.

Chapter 29 concludes the chapters that have been discussed in this book. This chapter highlights four domains: (1) smart outdoor production, (2) smart indoor production systems, (3) smart orchard management for increasing productivity and post-harvest management, and (4) non-destructive quality measurements. This chapter also outlines the future prospects of intelligence application toward sustainable agri-food systems associated with the SDGs and Society 5.0.

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The Tsukuba Global Science Week (TGSW) and Tsukuba Conference (TC) created a common platform hosted by the University of Tsukuba for global communication among researchers, universities, and industry. This joint "Agriculture x AI x IoT for Global Food Production" session has consistently contributed to collaboration over the years and has the privilege of hosting experts from diverse countries who generously share their experiences and expertise. Our focus has centered on integrating agriculture with transboundary approaches, including incorporating AI and IoT-based big data schemes to sustain food security. The invaluable knowledge exchange during these conferences has encouraged me to improve the second edition of the book with the goal of offering additional output and information from this TGSW/TC session. These improvements aim to make a substantial contribution toward aligning agriculture with the Sustainable Development Goals (SDGs) and the principles of Society 5.0.

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This second edition book is composed of 29 chapters. Bringing all the concepts together into one cohesive framework required tremendous effort, and this effort would not have been possible without the exceptional dedication of the team. In this regard, I would like to express special appreciation to my committed team of PhD and master's degree students for their tireless efforts in cross-checking, updating, and formatting the book. I extend my hearty gratitude to Munirah Hayati Hamidon, who demonstrated exceptional leadership by taking the lead in managing the team, efficiently distributing tasks, editing, drawing figures, and overseeing the progress of the book from the initial stage to the final submission stage. Additionally, Bryan Vivas Apacionado, R. M. Rasika D. Abeyrathna, Jiang Ailian, Liu Zifu, Nakaguchi Victor Massaki, Opasatian Ithiphat, Raka Thoriq Araaf, Sampurno Rizky Mulya, Pubudu Kahandage, Sudeshinie Piyathissa, and Arief Ameir Rahman Setiawan provided invaluable support in developing the content, literature review, layout formatting, and cross-checking the references for this book in the last few months. The success and outcome of this book were made possible by the considerable efforts of each team member. I am grateful for their unwavering support, assistance, and patience in the collaborative process, which ultimately led to the succinct production of this second edition. In addition to my dedicated team, I want to express my thanks to Nelundeniyage Sumuduni L. Senevirathne, Parwit Chutichaimaytar, and Arkar Minn, who are PhD students from our graduate school, for their assistance in cross-checking several chapters of this book. I feel incredibly privileged and fortunate to have such an outstanding team, whose contributions were instrumental in ensuring the successful completion of the book.

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Contents

Chapter 1
Digital Innovations in Agrifood Systems to Achieve the SDGs and Society 5.0

Abstract Digital innovation significantly contributes to the transformation of agrifood systems, aiming to achieve the Sustainable Development Goals (SDGs) and the realization of the Society 5.0 vision. The agriculture sector is currently witnessing significant breakthroughs due to the utilization of many technologies, including artificial intelligence (AI), robots, data analytics, mobile apps, blockchain technology, and digital twins. These innovations not only help in productivity enhancement, efficiency, and sustainability but also address societal challenges. These digital innovations contribute to achieving the SDGs by improving food security, reducing poverty, promoting sustainable practices, and fostering inclusive economic growth. Furthermore, these innovations in agrifood systems support the transition toward Society 5.0, in which humans and advanced technologies cooperate for sustainable development. This transition enables precision agriculture, autonomous farming, smart logistics, and intelligent distribution systems, creating more efficient and resilient agrifood systems.

Keywords Agrifood systems · Digital innovation · AI · Blockchain technology · SDG · Society 5.0

1.1 Introduction

Digital innovations in agrifood systems (AFSs) refer to the utilization of digital technologies, such as artificial intelligence (AI), machine learning, big data analytics, blockchain, and the Internet of Things (IoT), to address challenges and improve the efficiency, productivity, and sustainability of agricultural and food production processes (Ancín et al., 2022). These technologies are being used to optimize various aspects of AFSs, including precision agriculture, agricultural machinery and automation, and digital supply chain management. The goal of digital innovations in AFSs is to create a more sustainable, efficient, and resilient food system that can

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meet the growing demand for food for the expanding population while mitigating environmental impact and promoting social equity.

The advancement of digital innovations in AFSs can contribute significantly to achieving the Sustainable Development Goals (SDGs) and realizing the Society 5.0 vision (Fig. 1.1). The SDGs comprise 17 global goals endorsed by the United Nations in 2015, forming a crucial component of the 2030 Agenda aimed at securing an equitable and more sustainable future for the global population (Griggs et al., 2017; Biermann et al., 2017). These goals address various intersecting issues, such as poverty, hunger, health, education, gender equality, climate change, and sustainable economic growth. Notably, the integration of digital innovations in AFSs has

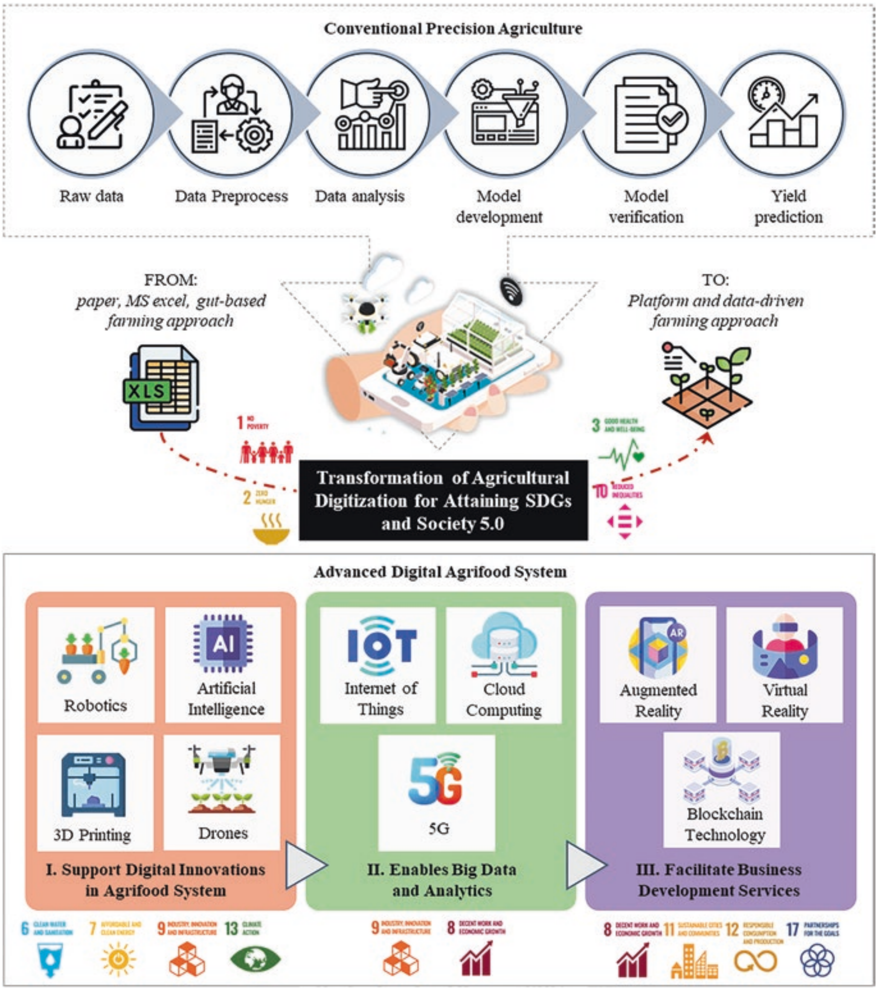

Fig. 1.1 Transformation of agricultural digitalization to achieve the SDGs and realize Society 5.0

the potential to contribute significantly to achieving several SDGs, including the following:

- SDG 2: Zero hunger can be achieved by improving food production, reducing food waste, and boosting food security.
- SDG 8: Decent work and economic growth can be realized by creating new job opportunities and improving productivity in the agriculture sector.
- SDG 9: Industry, innovation, and infrastructure can be realized by promoting innovation in agrifood systems and investing in digital infrastructure.
- SDG 12: Responsible consumption and production can be promoted by advocating for sustainable agricultural practices and mitigating the environmental impact of food production.
- SDG 13: Climate action can be advanced by curbing greenhouse gas emissions from agricultural fields and improving the resilience of food systems to climate change.

Moreover, the transformations of digital innovations in agriculture are aligning with the Society 5.0 concept by promoting the integration of digital technologies into all aspects of society, including the food system. This integration can support the development of a more effective and sustainable food system to better meet the needs of all stakeholders, from producers to consumers, while also promoting social equity and well-being. Society 5.0 is a concept that was initially envisioned by the Japanese government. It envisions a society where people can live harmoniously with technology to address societal challenges (Fukuyama, 2018). This concept recognizes the importance of digital transformation and the integration of new technologies to harmonize economic advancement with equitable social progress and a sustainable future.

Therefore, this chapter aims to elucidate the role of digital innovations, particularly in AFSs, in aligning with the SDGs and Society 5.0. This chapter outlines the different digital technologies being used in agrifood systems, their benefits, and their potential to address social, economic, and environmental challenges. It also discusses the challenges facing digital innovations in agrifood systems and future directions for research and development.

1.2 Digital Innovations in Agrifood Systems

1.2.1 Big Data Analytics

The rapid advancement of technology in various sectors, including the agrifood system, has led to an unprecedented amount of data generation. This exponential data growth has led to the introduction of the term "big data," referring to vast and complex datasets that are challenging to process using existing database management tools (Rejeb et al., 2021). Big data analytics is the process of accumulating, managing, and analyzing enormous amounts of data. As outlined by Manyika et al. (2011), the concept of big data encompasses three key components: volume, velocity, and variety. Then, an additional component was introduced by Kunisch (2016), denoted as the fourth V, which pertains to veracity. Notably, Chi et al. (2016) contributed a fifth component, valorization, thereby completing the five fundamental components of big data.

Volume refers to the enormous number of datasets generated daily from various sources, such as sensors and transactions. Velocity relates to the speed of generated datasets and their processing and analysis, often in real time, allowing for timely decision-making. Variety emphasizes the diversity of the datasets, including structured, unstructured, and semistructured information, posing challenges but also offering rich opportunities for analysis. Veracity signifies the accuracy and reliability of the datasets, ensuring that the data collected are trustworthy. Finally, valorization completes the process of transforming raw data into meaningful information and innovative insights, contributing to scientific discoveries and social advancements.

In the context of agrifood systems and the pursuit of the SDGs within the framework of Society 5.0, these five fundamental components of big data play important roles in shaping the future of agriculture and food production. The sheer scale of data (volume) generated by agrifood systems, from crop monitoring sensors to supply chain transactions, presents an opportunity for in-depth analysis. The speed at which these data are generated and processed (velocity) allows for real-time decision-making, enabling farmers to respond swiftly to changing conditions and market demands, thereby contributing to the achievement of SDG 2 (zero hunger) by improving food production and reducing waste. Diverse types of data (variety), ranging from weather patterns to consumer preferences, provide a comprehensive view of the agrifood ecosystem, aiding in sustainable practices aligned with SDG 12 (responsible consumption and production). Ensuring the accuracy and reliability of these data (veracity) is critical for informed decision-making, especially in addressing climate-related challenges (SDG 13: climate action). Additionally, the valorization of these data, through advanced analytics and AI-driven insights, fosters innovation in agrifood systems, creating new economic opportunities and supporting the achievement of SDG 8 (decent work and economic growth). By applying predictive analytics to integrated big data systems, optimization of food quality, safety, and security can be achieved.

1.2.2 Internet of Things (IoT) and 5G Wireless Networks

Big data and the Internet of Things (IoT) are two interconnected technologies that have emerged as a central domain in the global information and communication technology (ICT) industry (ur Rehman et al., 2019). The IoT represents an emerging communication paradigm wherein many devices engage in collaborative data exchange within an integrated structure or function autonomously as separate entities. Precision agriculture, at the level of farming operations, encompasses the utilization of information and communication technologies to enhance the management of agricultural products, livestock, and natural resources, thereby optimizing farm performance at the economic, social, and environmental scales (Liu et al., 2021). This approach relies on the deployment of various sensors and IoT equipment within agrifood systems. For instance, IoT-enabled sensors are strategically installed on agricultural fields to inspect essential variables such as weather conditions, soil health, crop status, and livestock well-being (Sinha & Dhanalakshmi, 2022). The integration of big data with IoT concepts enables the collection, analysis, and utilization of the large amounts of data generated by IoT devices to derive valuable insights and enhance decision-making processes.

To establish a balance between global demand and supply in the food supply chain, IoT sensors and other information and communication technologies may be implemented to effectively monitor food quality, safety, and security (Lezoche et al., 2020; Abideen et al., 2021). Integrating the IoT in AFSs holds significance for enhancing the flexibility of food supply chains by generating a wealth of real-time data that can be analyzed using advanced predictive analytics. By generating real-time data, which can be analyzed using advanced predictive analytics, the IoT equips AFSs with the ability to determine vulnerabilities in the supply chain promptly. This proactive identification allows for the implementation of necessary measures to maintain the integrity of the food supply. Furthermore, IoT applications in AFSs extend to preserving the quality of fresh produce, ensuring compliance with food safety regulations, and consequently, reducing food waste while bolstering food security (Tagarakis et al., 2021). Nevertheless, there are ongoing issues associated with the use of IoT devices, both at the agricultural level and across the entirety of the food supply chain. Addressing these challenges is necessary to fully unlock the value of the IoT in the food industry.

To facilitate the transition toward Society 5.0 and fulfill the SDGs in the digitalization of AFSs through the IoT, there is a need for a telecommunications network that enhances connectivity and improves the distinction between digital and physical spaces. Most of the current network communication systems, such as 3G/4G, Wi-Fi, long-range wide area networks (LoRaWANs), and the narrowband Internet of Things (NB-IoT), encompass restricted accessibility and bandwidth, leading to latency issues that cause delays in data transfer, hindering efficient data communication (Tang et al., 2021). Addressing this limitation requires the incorporation of greater capacity to support the increasing number of interconnected devices necessary for the advancement of smart agricultural practices. Hence, the emergence of 5G communication networks has the potential to make connectivity more affordable and accessible for a wide range of stakeholders. The fifth generation of wireless networks, referred to as 5G, is the most recent advancement in wireless technology. It aims to provide users or devices with ubiquitous information accessibility and the capability to exchange data in any location and at any time (Andrews et al., 2014).

The remarkable capabilities of 5G networks, including high-speed data transfer and low latency, make these networks suitable for supporting machine-to-machine communications within the agrifood supply chain (van Hilten & Wolfert, 2022). For example, 5G's efficient connectivity can be advantageous for deploying automated guided transporters in food distribution operations. The emergence of 5G technology in the food industry holds significant promise for transformative advancements in connectivity, data transmission, and operational efficiency, therefore enhancing the degree of communication within the AFS.

Moreover, the integration of 5G and the IoT enables real-time data collection, analysis, and communication, empowering the AFS to make more informed decisions, mitigate risks, and respond promptly to challenges. This increased productivity and flexibility can expedite progress toward the achievement of Society 5.0 and the SDGs, particularly by contributing to addressing food security issues and ensuring the availability of safe and nutritious food for everyone while fostering sustainable practices throughout the food supply chain.

1.2.3 Artificial Intelligence in Digital Agrifood Systems

Artificial intelligence (AI) is a digital technology that is making rapid progress in the agricultural sector. The agricultural sector is projected to experience substantial investments in AI in the coming years, with an anticipated 23.1% compound annual growth rate (CAGR) from 2023 to 2028, indicating the increasing recognition of AI's potential to transform the agriculture market (Market Research Report, 2023). The application of AI is revolutionizing various aspects of farming, and AI has been applied in some key areas in agriculture, such as in robotic farming, crop

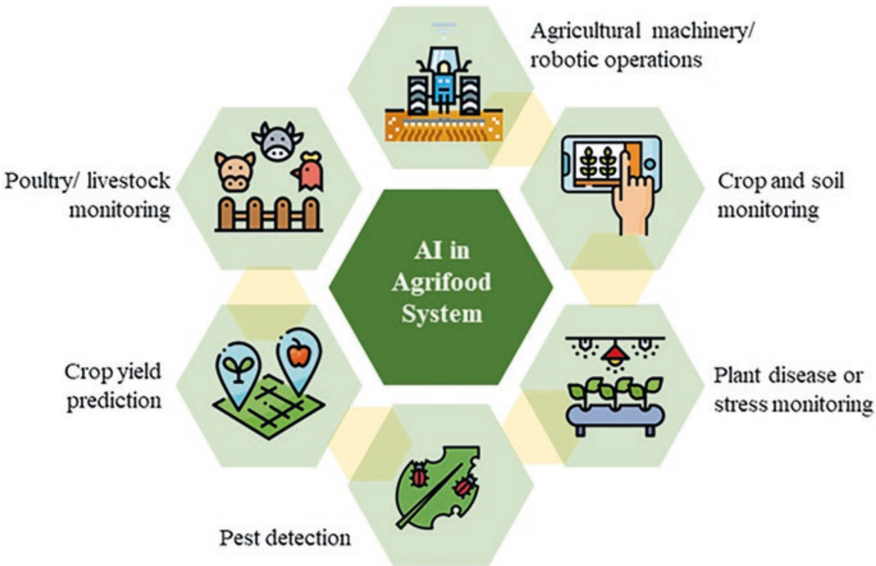

Fig. 1.2 Applications of AI in agrifood system

monitoring and disease detection, crop yield and harvesting prediction, and livestock monitoring (Fig. 1.2).

AI is being used to analyze data obtained from sensors, drones, satellites, and other devices to provide real-time insights into soil conditions, crop health, water usage, and more (Dharmaraj & Vijayanand, 2018). Such insights help farmers optimize the use of resources and apply interventions only where and when necessary, reducing costs and environmental impact. Moreover, AI and machine learning can be employed for monitoring crops and identifying stress or diseases by training on a large dataset of crop images (Fig. 1.3) (Hamidon & Ahamed, 2022). These technologies extract features to facilitate the precise and efficient identification of diseases, pests, and nutrient deficiencies. Such identification enables farmers to implement early interventions to mitigate these issues, minimize crop losses, and improve overall yields.

Furthermore, AI plays a valuable role in yield prediction and harvesting optimization. Algorithms can be used to process historical and real-time weather, soil, and crop growth data to help farmers predict crop yields accurately (Shaikh et al., 2022). This information helps farmers optimize harvesting schedules, plan logistics, and estimate market supply. With the prediction information obtained by AI analysis, farmers are well equipped to strategically plan when to harvest their crops, manage logistical operations more efficiently, and offer more accurate estimates of the supply that they can contribute to the market. All of this leads to better and more precise resource allocation and improved profitability.

The application of AI has also been extended to animal farming and production to help farmers overcome longstanding challenges as well as modern obstacles and limitations (Neethirajan & Kemp, 2021; Bao & Xie, 2022). For example, AI technologies provide poultry farmers with the opportunity to acquire real-time insights into their farming operations (Neethirajan & Kemp, 2021). These insights enable farmers to effectively monitor and regulate crucial environmental conditions such as

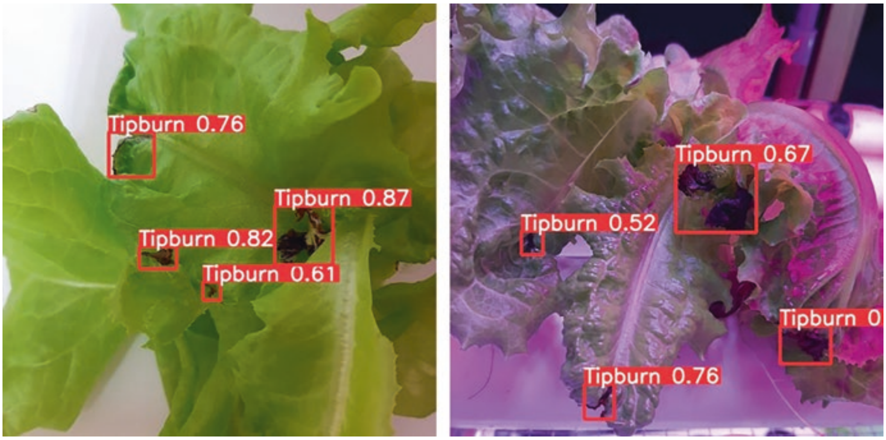

Fig. 1.3 Example of AI being used to detect nutrient deficiency in plants