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Leveraging edge artificial intelligence for sustainable agriculture

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Effectively feeding a burgeoning world population is one of the main goals of sustainable agricultural practices. Digital technology, such as edge artificial intelligence (AI), has the potential to introduce substantial benefits to agriculture by enhancing farming practices that can improve agricultural production efficiency, yield, quality and safety. However, the adoption of edge AI faces several challenges, including the need for innovative and efficient edge AI solutions and greater investment in infrastructure and training, all compounded by various environmental, social and economic constraints. Here we provide a roadmap for leveraging edge AI at the intersection of food production and sustainability.

The future of humankind depends on secure, sustainable and safe methods to produce food, energy, water and industrial raw materials, as well as their efficient use[1]. An increase in global food production of at least 60% is needed to ensure the planet's ability to feed the growing world population, which is expected to reach 9 billion by 2050[2]. However, sustainable agriculture is facing three major challenges, making the realization of the required increase in food production difficult, if not unobtainable. The first challenge relates to the resources required for the food production process itself. Increasing agricultural production comes at a cost to nature and the environment, with habitat loss, environmental damage and exploitation being important threats to ecosystems and biodiversity[3]. For example, over the past decade, the rate of conversion of natural forests into other land uses, including agricultural systems, was approximately 13 million hectares per year[4]. Crop genetic diversity has been eroded, and currently 80% of threats to mammal and bird extinction are due to agriculture[5,6], although technology-based intensification of agriculture often results in a net saving of land areas[7]. Agricultural water use accounts for approximately 72% of all freshwater withdrawals globally[8], which can lead to unsustainable water use in water-stressed regions and exacerbates food insecurity. Moreover, intensification of agriculture increases fossil-fuel-based energy consumption by about five times compared with low-input agriculture, with concerns over local energy access in a world exposed to recurrent polycrises[9].

The second challenge is linked to external factors, which most often are beyond farmers' control. The challenges consist of (1) environmental factors such as climate variability and change, soil degradation and loss of agricultural land[10] and (2) economic and political factors, including political instability, government restrictions and inflation. For example, changes in weather patterns and in the frequency and intensity of extreme climate events are being experienced increasingly in several regions worldwide[11], resulting in noticeable agricultural losses, increases in infestation of pests and epidemics of diseases or emergence of new ones, not to mention the introduction of exotic pathogens, which can negatively impact agricultural production in new areas.

The third challenge is centred around the users and consumers. This consists of human habits such as overconsumption, food waste,

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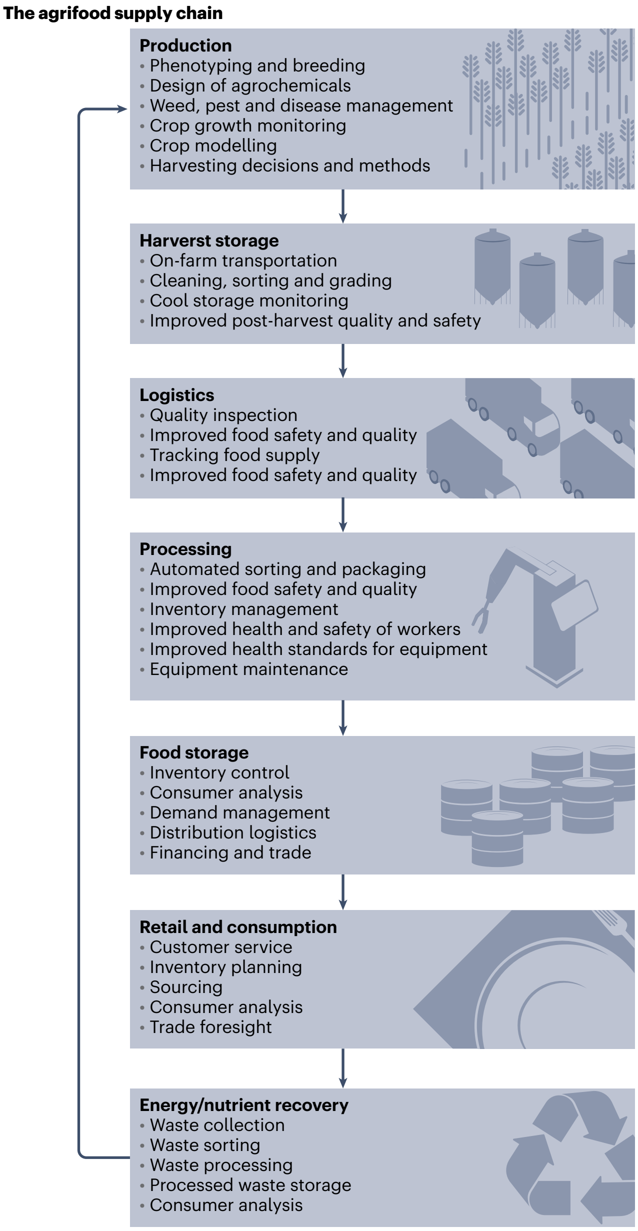

Fig. 1 | The agrifood supply chain and applications of AI. Edge AI has the potential to improve efficiency, productivity, quality, safety and sustainability across the entire agrifood supply chain, from food production, processing, storage, distribution and retail, and consumption to the recovery of nutrients and energy from food waste. In this Perspective, an emphasis is placed on farming and agriculture. Figure adapted from ref. 61, MSU.

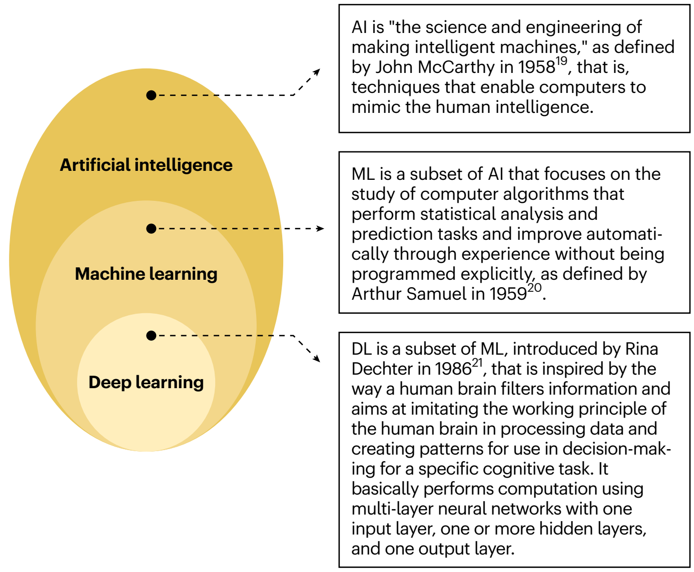

Fig. 2 | History of AI deployment. Research on AI and ML started in the late 1950s. However, its deployment started only about a decade ago as it requires three major components: large datasets, training algorithms and high-performance computing platforms that are able to perform the processing in an affordable time. By the early years of the 2000–2010 decade, the problem was not obtaining data but rather making use of the data, putting pressure on developing advanced algorithms to extract the right information from the available data. By the late 2000–2010 decade, many advances in algorithms and fundamental theory of AI had been made, and at the same time the semiconductor industry discovered computing chips that could notably provide high computing throughput compared with what was offered in the conventional computers at the time. Hence, the deployment of AI area commenced. Today, AI, ML and DL are driving game-changing capabilities with huge impacts on various aspects of society, including farming and agriculture, self-driving cars, cancer diagnosis, accelerating drug development, voice-activated devices, self-healing digital grids and self-replicating robots.

varying food preferences and dietary restrictions among consumers, as well as their willingness or reluctance to pay for certain agricultural products or services[12,13]. In addition, there may be cultural or societal factors that impact the consumption patterns and habits of individuals in different regions, posing unique challenges for growers and agricultural commodities distributors[14].

Addressing these diverse challenges requires a profound transformation of agricultural production that considers the interconnectedness of the agrifood supply chain with all stakeholders, including the social, economic and environmental components[15]. The deployment of digital technologies is being heralded as a powerful tool for surmounting some of these challenges as they can support knowledge-based decision-making and availability of knowledge at a large scale throughout the agrifood supply chain[16,17] (Fig. 1). A digital technology that has this potential is edge computing (the practice of processing and analysing data close to the source or edge of the network, such as on local devices or edge servers) combined with artificial intelligence (AI), called edge AI[18]. Edge AI entails the deployment of connected computing devices at the individual production unit scale (the farm). These devices are equipped with sensors that continually gather data and intelligently process the information locally to trigger specific actions via dedicated actuators or to provide decision support in real time.

Considering the current emphasis on sustainability and efficiency in agriculture and food production, we provide a comprehensive overview of the potential applications of edge AI in promoting sustainable food production and discuss the challenges and limitations for the successful implementation of the technology. By highlighting the benefits of edge AI in areas such as resource-use efficiency, management of biotic and abiotic risks, and enhanced farming productivity, we describe a roadmap for how edge AI can be used to improve agricultural practices towards greater sustainability. Moreover, we emphasize the importance of transdisciplinary collaboration and the need to address ethical and social implications of automation and data-driven decision-making as integral to the ongoing discussion on the role of AI in agriculture and how edge AI can serve as a valuable resource for policymakers, researchers and practitioners working towards sustainable food production.

AI in agriculture

While research on AI, machine learning (ML) and deep learning (DL) started many decades ago[19–21], using AI in agriculture is still in its infancy (Fig. 2).

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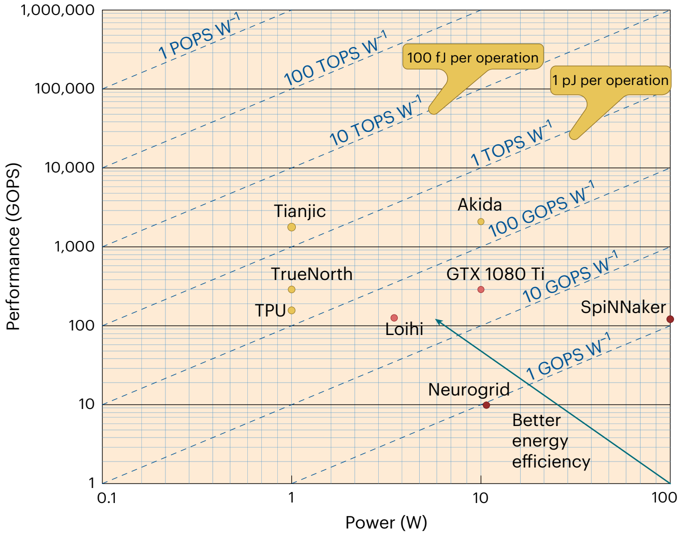

Fig. 3 | The energy efficiencies (operations per watt) of state-of-the-art computing chips used for AI/DL applications. The performance of state-of-the-art chips is far from achieving the 1 fJ per operation needed for edge AI (1 fJ = 10^{-15} J). GOPS, giga operations per second; POPS, peta operations per second; TOPS, tera operations per second.

Hardware and development potential for AI in agriculture

Today's AI applications run primarily on powerful and expensive cloud computing platforms making use of different architectures supporting some form of DL. One end of the spectrum uses various types of general-purpose central processing unit (CPU) and graphics processing unit (GPU) architectures, with limited DL support[22,23]. At the other end of the spectrum are dedicated digital or analogue implementations of DL systems, several examples of which have been developed recently, including IBM TrueNorth[24], Intel Lohi[25] and Morphic[26] (Fig. 3). However, the hardware architectures of these DL systems face major challenges, including that they are power hungry, are expensive (mainly targeting cloud and data centres), suffer from high leakage of power (due to volatile complementary metal–oxide–semiconductor technology nodes) and consume a lot of chip area as large amounts of memory are distributed among many processors on a single chip, and that off-chip memory communication burns power and taxes memory bandwidth[27]. Today's DL systems are extremely resource demanding (Fig. 3) and environmentally unfriendly. For example, a single training of ChatGPT-3 (making use of 175 billion parameters) takes 2 weeks and uses 9,200 GPUs[28], consuming 1,287 MWh (ref. 29); this energy is enough to power a town of 16,000 people for 24 hours. The associated carbon release is equivalent to the amount released by 1,300 cars operating non-stop over the same training period of 2 weeks. The energy demand issues not only make existing hardware architectures unsuitable for edge AI applications (in which cost and energy efficiency are critical), but also render AI applications unsustainable due to their huge resource consumption. Even the most recently developed AI/DL systems have an energy efficiency that is too poor compared with what is needed for edge AI, which is approximately 1 fJ per operation or less[27] (Fig. 3). Current hardware architectures based on traditional device technologies are not able to provide the computation efficiency and capability needed for edge AI. Thus, new architectures based on new technologies, together with their associated programming models and compilers, are urgently required to unlock the full potential of edge AI.

One of the potential solutions that could enable edge AI for sustainable agriculture is the new computing paradigm referred to as computation-in-memory (CIM) based on emerging non-volatile devices such as memristors[30]. CIM tightly integrates computation and storage of data in a memory crossbar architecture supporting massive parallelism. As the storage and computation are integrated together, the communication bottleneck between storage and processing units is substantially reduced[31]. Moreover, recent work based on CIM chip prototyping has demonstrated that energy efficiencies of ×100 to over ×1,000 improvement, compared with the current state of the art, are achievable[32], which is the efficiency that edge AI typically needs. Hence, deploying edge AI solutions in agricultural systems is becoming closer to a reality.

Prerequisites for AI access to farmers

Production of food starts with farmers; likewise, edge AI solutions should start at the farm level with the farmers. Examples of the required data and processes suitable for farmers are (1) real-time 24 hours/7 days a week data gathering in a secure manner through the monitoring and measurement of key parameters (for example, climate variables, soil moisture and nutrient content, pest or disease occurrence, crop development, and nutrient uptake); (2) processing these data, ideally locally 'at the edge' of where the data are collected to prevent any unexpected disconnects from the internet or the cloud; and (3) on the basis of the AI-driven interpretation of the data, acting using dedicated or customized actuators to apply a required input or provide a decision-making process directly to the farmer or to agricultural extension officers, the latter particularly in low-income countries. While research and innovation in data generation (for example, using appropriate sensors) and AI algorithms have realized good progress and are very promising[33], energy-efficient hardware remains a major bottleneck preventing the deployment of edge AI at a larger scale[34]. The development of edge AI-supported agriculture has unique attributes and characteristics that put special requirements on the table: high-quality data, appropriate algorithms and energy-efficient computing hardware that is capable of running the algorithms in an economically affordable manner. These requirements should be solved in a cost-effective manner before advancing edge AI agriculture from niche projects to concrete, successful deployment on a large scale, dramatically changing how agriculture operates.

Potential of edge AI-supported agriculture

Edge AI will have a profound transformative effect for the agrifood supply chain as a whole[17,35]. It has the potential to increase productivity, reduce resource utilization and enhance sustainability by better using information from different sources (Fig. 4).

Increase productivity

Edge AI offers notable potential for discovering desirable traits and risk factors in plant breeding, evaluating and meeting nutrient and water demand, monitoring and managing biotic and abiotic stresses affecting crop and livestock production, improving crop harvesting and grading, among others. For example, the integration of multimodal cameras and associated AI algorithms enables high-throughput crop phenotyping for next-generation cultivars with desirable traits[36]. By analysing data from sources such as remote-sensing platforms, climatology, soil and plant/animal health monitoring, farmers can gain valuable insights into their agricultural system health and potential productivity[37]. This enables early intervention to prevent crop/livestock loss and for pest and disease management, even pre-symptomatically in real time[38], resulting in, for example, site-specific application at the optimum time point. Edge AI allows for automation of field operations through the deployment of robotics and mechatronic automation, thus reducing human intervention and improving workplace safety[39,40]. Moreover, employing ML and DL algorithms in crop growth modelling can also help simplify model parameterization by making use of the data acquired from multiple sources and improves the model's accuracy of yield prediction[41]. Interest in the use of AI/ML- and DL-based approaches for crop growth modelling and yield prediction is evidenced by the increasing number

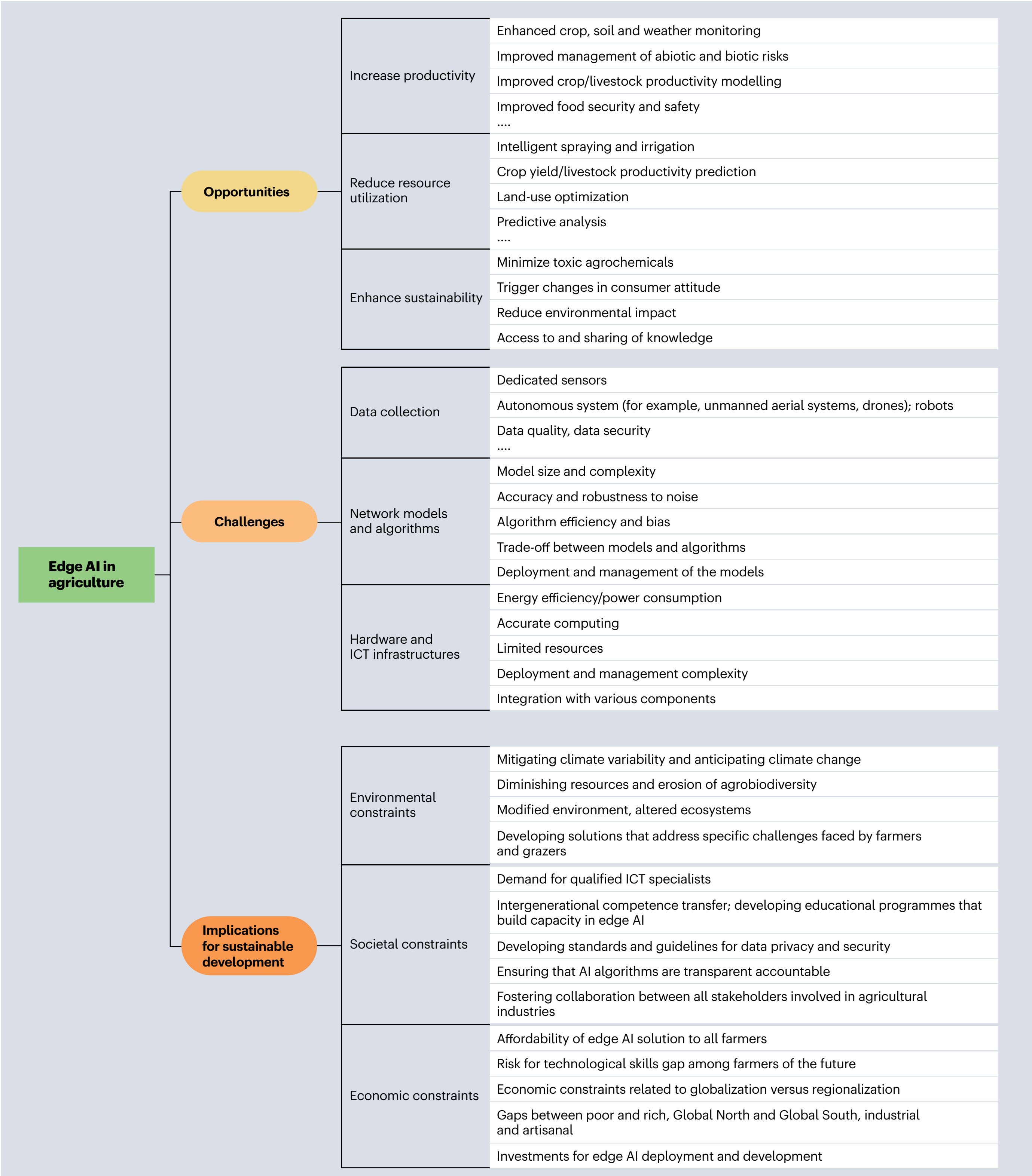

Fig. 4 | Edge AI presents a range of opportunities, challenges and implications for sustainable agriculture. The adoption of edge AI-based solutions will result in a huge added value both for the food industry (for example, increased productivity at lower resource use) and for sustainable management of agricultural systems. By recognizing the complexities and tensions inherent in adopting edge AI in agriculture, establishing AI task forces, implementing effective governance schemes, and investing in both the development and deployment of edge AI-based solutions, researchers, practitioners and policymakers can steer the development of edge AI towards a sustainable future.

of related publications over the past decade[42]. AI/ML- and DL-based approaches are increasingly used as they offer an alternative framework to process-based models and increased flexibility for their integration into automated decision-support systems[42]. By leveraging edge AI, farmers can enhance the efficiency and productivity of farming operations while minimizing their environmental impact.

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Reduce resource utilization

To sustainably improve crop production, several key areas must be optimized, given that varying levels of inputs such as water, energy, agrochemicals and human capital are required for day-to-day farming activities. Such resource-use optimization can be achieved through predictive analysis to inform and/or support data-driven decisions. Leveraging the integration of sensors and edge AI (for example, in smart farm vehicles and machines) will facilitate the precise dispensation of optimal quantities of irrigation water and agrochemicals to individual plants or specific areas, thus advancing sustainability strategies on farms through the reduction of water, fertilizers and agrochemicals. By targeting the specific quantities of water, fertilizers and agrochemicals needed by a crop, edge AI can also contribute to sustainable and environmentally friendly agricultural practices[37]. Labour-intensive tasks such as the manual scouting of plant diseases or the monitoring of crop phenological stages can be alleviated through AI-based solutions[43]. Leveraging edge AI for water and nutrient needs, as well as weed, pest and disease management, can lead to more environmentally friendly and sustainable practices while maximizing productivity.

Enhance sustainability

The adoption of edge AI for agricultural production will enable sustainability and associated ecological benefits in a myriad of ways. It will help minimize the use of toxic agrochemicals, trigger changes in people's attitude towards food (re)usage and food waste, and optimize use of freshwater and land. These improvements would reduce the overall environmental footprint while continuing to feed the population nutritiously, safely and sustainably. Furthermore, adopting edge AI in agriculture can allow for a transformative approach to AI that integrates sustainability considerations into both its application for achieving the sustainable development goals and its own operational aspects, for example, smarter use of resources, and reduction of greenhouse gas emissions, energy consumption and carbon footprint, ensuring responsible data usage throughout the entire AI life cycle.

Edge AI in practice

Deployment of computer vision

In-field high-throughput plant phenotyping, based mainly on computer vision, has been considered a promising technology to enhance the efficiency and accuracy of assessment of the growth dynamics of crop plants under abiotic and biotic stresses[36]. For example, a close-range multi-camera system based on state-of-the-art imaging technologies was developed to characterize the growth dynamics of wheat varieties[44]. The multimodal vision system, composed of two red–green–blue cameras, a multispectral camera array and a thermal camera, was embedded on a modular, motorized platform to allow the sensors to monitor micro-plots in a field trial with one remote operator, or autonomously with a vision-based navigation system. Canopy height maps were generated from both colour cameras using stereoscopic vision and were further processed to estimate relevant morphological traits such as leaf area index and the height descriptors of wheat organs[44]. On the basis of the canopy-to-camera distance, deduced from the stereoscopic data, multimodal image registration can be performed to fuse colour, height and spectral and thermal descriptors at the pixel scale[45]. While conventional analysis consisted of combining traits independently deduced from each imaging technology, certain approaches aim at extracting new and complex agronomic traits from image fusion relating to each plant organ[46]. Compared with human vision for observation, digital technologies have shown the potential to bring automation, objectivity and additional agronomic information to better understand crop growth dynamics[36].

Deploying the Internet of Things

By using the Internet of Things (IoT) (defined as interconnection via the internet of computing devices, enabling them to send and receive data) and edge computing, farmers will be able to monitor their crops and livestock in real time, track environmental conditions, and reduce water usage and pollution[47]. Various case studies have demonstrated the potential of using edge AI in agriculture. For example, in viticulture, IoT monitoring has been used to anticipate and manage vineyard diseases[48]. Other successful implementations include the Granular edge AI platform that provides farmers with insights into crop health and yield potential[49]. Animal production can also benefit from AI, and research efforts have demonstrated, at the experimental stage, the potential of AI for animal behaviour detection and recognition[50]. The timely identification and handling of factors limiting crop and livestock productivity can enhance the productivity itself and the resulting profit. By combining IoT and edge computing, agriculture can be made more sustainable and efficient, enabling farmers to make informed decisions about their management practices or further allowing the automatization of agricultural activities such as irrigation and protection by optimizing the trajectories and correcting in real time different unmanned systems[51]. Moreover, AI-enabled robots are being used to provide real-time insights into food quality and safety during storage, automate production lines and improve quality control, packing and labelling[52]. These AI- and robotics-supported advances are enhancing production, quality, traceability and safety, sustainability, and efficiency across the entire agrifood sector[52]. It is expected that the global market volume for food robotics will grow by around 5.4 billion units by 2030 (ref. 53).

Navigating edge AI challenges

For edge AI to be deployed broadly in agriculture, many scientific challenges must be solved. These include (1) data collection, (2) models and training algorithms, and (3) hardware and information and communications technology (ICT) infrastructure (Fig. 4). These three key factors form a vicious circle; that is, the larger and more complex the dataset, the more complex are the network models and algorithms. This, in turn, requires increasingly powerful and high-performance hardware (which becomes too power hungry). For edge AI in agriculture, advances must be made in all three aspects to provide sustainable and cost-effective solutions.

Data collection

Seamless and reproducible data collection processes are crucial for any AI applications, thus the need to develop and use mechanisms suitable to collect relevant data that can be fine-tuned for farming. Dedicated (wireless) IoT sensors such as those targeting field conditions (weather, soil quality, plant/animal health condition) can be deployed in remote-sensing platforms (for example, satellites, unmanned aerial systems) and autonomous systems (for example, robots) to assist in data collection. IoT sensors deployed on these platforms allow for the automation and provision of real-time information regarding different aspects of the crop or livestock farming system. The acquisition of the remotely sensed data can be based on multispectral, hyperspectral, thermal, and light detection and ranging (LiDAR) technology. However, some of these technologies, such as LiDAR, are still too expensive and power hungry, hence the need to make them affordable and have a lower power demand while maintaining or increasing their reliability and accuracy. Note that data quality is of paramount importance for the overall performance of edge AI solutions. As data collection devices may generate noisy or low-quality data, special attention and countermeasures should be put in place to ensure that the data quality is good enough for the targeted ML/DL algorithms and desired accuracy. Equally important is the protection of such data. Farmers may not want their sensitive farm business data to be accessed; hence, security measures against any potential attacks should be implemented and provided as options to farmers.

Network models and algorithms

Building appropriate network models and developing AI algorithms extracting meaningful information from the collected data are crucial for applying AI. In fact, this is an important trade-off that is strongly application dependent. For example, for agriculture, we would like to produce a model that is efficient: a model that is cheaper to design in hardware or software, energy efficient to compute, easier to train, yet reliable and accurate enough for the purpose. Choosing which model to use and/or adapting it for edge AI is a key problem today. High-precision AI models are very large and require large memories, while the memory footprint of edge devices is typically very well optimized. Therefore, resource-efficient edge AI models, including collaborations between small (at the edge) and large (in the cloud) models via data offloading, that adapt to changing environments and are tailored for sustainable farming should be explored. In fact, the collaborative hierarchy within the different levels of edge–cloud synergy (for example, end device, edge node, network and cloud data centres) may provide an optimized energy consumption and accuracy as it enables the exploitation of all available resources across the hierarchy[54]. The resulting performance should be sufficient for the targeted in-field operations. In addition to resource-efficient edge AI models, the development of resource-efficient and unbiased training algorithms is of profound importance. It is well known that the quality and efficiency of an AI solution strongly depends on both the quality of data provided and the training algorithms[37]. If the algorithms themselves are faulty or biased, they will show inaccurate results, making them unreliable. Biases emerge mainly from the partial way programmers have designed the algorithm by favouring some desired or self-serving criteria. Algorithmic efficiency is a measure of how well an algorithm uses the available resources, such as time, memory or energy, to solve a problem. There is a trade-off between algorithmic efficiency and AI model performance. For example, one might be able to increase the AI model performance by using more sophisticated algorithms, but this might increase the resource consumption and execution time. Conversely, one might be able to reduce the resource consumption and execution time by using simpler or faster algorithms, but this might decrease the accuracy or functionality. Finding the optimal balance between algorithmic efficiency and AI model performance for agriculture is very important due to limited resources at the edge. However, it is a complex task; it depends on various factors such as the specific problem, data characteristics, environment constraints and user preferences. Last, deploying and managing ML models on edge devices in agriculture is a complex task and will require specialized tools and expertise.

Hardware and ICT infrastructure

Edge computing not only needs sharpness in AI models and algorithms but also has a huge dependency on the hardware and infrastructure support. One of the major concerns we are facing today is the lack of energy-efficient computer hardware that could enable edge computing while considering limited resources; edge devices typically have limited resources, including processing power, memory and storage. There is a lot of ongoing research and development into new computing paradigms and new device technologies, and preliminary results indicate that these could substantially boost the energy efficiency at the edge[32]. However, such technologies inherently suffer from various non-idealities[55] (for example, variability and drift in their electrical parameters) that could further reduce the accuracy. This calls for the development and integration of software and hardware self-healing mechanisms in such computing devices, mechanisms capable to detect faults or failure and fix them without human intervention. These will enable the computing system to maintain its operational status while guaranteeing the required reliability and accuracy. In addition, the deployment and management of edge AI devices across widely distributed devices could be computationally burdensome. Simplifying processes such as remote device management, software updates, edge application deployment and monitoring is crucial for efficient operations. Appropriate ICT infrastructure and edge management platforms and automation tools can streamline these processes. Wireless technologies, such as 5G, can be an integral part of such infrastructure due to higher data rates, larger coverage areas and adaptability to heterogeneous communication environments[56]. Moreover, seamless integration of AI edge devices with various components will be a tedious task; developers from different domains use different frameworks and models to build out the applications, and companies might also use third-party tools that need integration with the new hardware and software being used for edge AI.

Implications for sustainable development

Edge AI in agriculture necessitates a dual focus. First, it entails leveraging AI to drive progress towards greater productivity, biodiversity conservation, climate resilience, environmental health and poverty reduction (particularly in low-income countries). Harnessing the potential of AI in addressing these global challenges will enhance our collective efforts towards sustainability. Second, it explicitly acknowledges the need to promote the sustainability of AI training and usage. This encompasses considerations such as reducing energy consumption, minimizing carbon emissions and ensuring responsible data usage throughout the entire AI life cycle. As agriculture becomes more technology dependent, it is crucial to consider the potential implications for sustainable development in relation to all three pillars of sustainability: the environmental, social and economic aspects (Fig. 4).

Adapting to environmental challenges

Edge AI will have to show agility to adapt to climate change as it might face extreme weather conditions or novel farming issues not previously experienced across a spectrum of production constraint areas (for example, invasive species, physiological changes under elevated CO_2 concentrations, high temperatures, erratic rainfall). Training data from current areas that have warm climatic conditions could be used to determine how to approach future problems in the cooler areas subject to warming, or to suggest new, better adapted farming in areas impacted by climate change. Adopting edge AI should help effectively address and mitigate environmental and climate challenges.

Edge AI solutions that are tailored to address specific challenges faced by farmers can improve their adoption and effectiveness. For example, edge AI solutions that help farmers monitor soil moisture levels or detect pest infestations early can be particularly useful. Moreover, such solutions must be designed with an understanding of the social, economic and cultural factors that influence farming practices to ensure that they are effective and practical.

Societal constraints and challenges

A new all-technological paradigm for agriculture may one-sidedly promote the industrial model of centralized food production and marginalize smallholder farmers. While promising to increase global food production and to reduce wastage of resources, there is a risk that edge AI in agriculture may further exacerbate the digital divide between the Global North and the Global South, rich and poor, industrial and artisanal. In the Global South, it may also hasten the ongoing displacement of local, family subsistence agriculture by large-scale industrial enterprises that turn smallholders into agricultural labourers[57]. To ensure that farmers in rural areas, or in less-developed regions of the world, can benefit from edge AI technologies, policies that facilitate access to reliable and affordable broadband must be developed. In addition, funding mechanisms that support the development of edge AI technologies that are accessible and affordable to small-scale farmers can help bridge the digital divide.

The collection and analysis of data are at the core of edge AI. Therefore, it is essential to develop standards and guidelines that ensure the privacy and security of data collected from farms. This could involve implementing encryption and other security measures to protect data as well as establishing clear policies for how data can be used and shared. Such guidelines must be informed by input from farmers, technology providers and policymakers to ensure their effectiveness and relevance. A first approach towards standards and guidelines is based on the findability, accessibility, interoperability and reusability (FAIR) data principles[58]. The opacity of AI decision-making processes poses an important challenge for the adoption of AI in agriculture. To address this, tools can be developed to audit and explain AI decision-making processes. Establishing mechanisms for resolving disputes or complaints related to algorithmic bias is another approach that can improve transparency and accountability. Moreover, involving stakeholders, including farmers, in the development and validation of AI models can help ensure that the models are accurate and fair.

A transdisciplinary approach that brings together experts from various fields, including computer science, technology, agriculture, health, social sciences and policy, as well as farmers, is needed to realize the full potential of edge AI in agriculture. Farmers need to be involved in the design and development of edge AI technologies to ensure that the technologies meet their needs and are practical for use on their farms. Technology providers must collaborate with end users and policymakers to ensure that regulations and standards do not hinder innovation while protecting farmers' interests. Such collaborations can also help identify and address potential issues, such as algorithmic bias, before they become systemic problems. Policymakers must ensure that regulations and standards support innovation and the protection of farmers. The adoption of edge AI in agriculture requires adequate information acquisition efforts, specialized knowledge and skills. Therefore, educational programmes that build capacity in edge AI for farmers, next-generation farmers and other stakeholders must be developed. Such programmes can help farmers understand the potential benefits of edge AI, how to use and interpret data collected by edge AI technologies and how to integrate edge AI into their farm management practices. Education programmes must also be incorporated into universities, colleges and early-phase education.

In addition, the potential impact on traditional farmer knowledge and intergenerational competence transfer must be considered. While AI solutions can support farmer tasks in observation, monitoring, diagnostics, decision-making and action, the farmers of tomorrow may become mere 'button pushers', lacking a deep understanding of production processes, resulting in loss of knowledge and competence in 'traditional hands-on' and low-input agriculture, further disconnecting them from the agricultural environment. In addition, edge AI may reduce the need for crop specialists (plant pathologists, entomologists, agronomists and so on) and field scouts, further impacting these industries and the applied research and extension support that is currently provided by these trained individuals. All these farmer- and specialist-related aspects of the impact of edge AI will require careful navigation and collective dialogue and must be framed in a way that encourages constructive discussion rather than contentious debate. Thus, challenges lie in the (initial and continuous) training of farmers and extension officers and in the maintenance of the systems, including troubleshooting. Developing sensitive approaches to resolve any disputatious issues will need to be sought. Addressing these questions and concerns will be crucial to realizing the full potential of edge AI in agriculture and promoting sustainable practices.

Implications from an economic perspective

From an economic standpoint, edge AI in agriculture presents compelling advantages, yet the ecological benefits that can be realized extend far beyond the mere mitigation of water, energy and agrochemicals overuse. While AI can help protect ecosystems and preserve biodiversity, the social dimension must also be considered[59]. The digitalization of society has already led to changes in the labour market, with a growing demand for qualified IT specialists, and impacts on employment in some sectors where digitization, automation and robotization replace jobs once done by members of the working and middle classes. This trend is also impacting agriculture, particularly small and medium-sized enterprises in family farming, especially in low-income countries[60].

Considering the development of edge AI in agriculture, there exists a potential risk for a technological skills gap among farmers of the future, favouring those with a background in IT and engineering and potentially leaving others at a disadvantage. Furthermore, will AI solutions be accessible to all farmers, regardless of their farm size, annual turnover or geographical location? Will they be affordable and manageable for smallholders, and can they be used in local, diversified and mainly artisanal systems? How can initial and continuous training sessions be organized for technologically unskilled farmers, and how can maintenance and troubleshooting be ensured for systems that traditional farmers in less-developed regions may not be able to manage themselves? To ensure access to edge AI solutions to all farmers, especially those in low-income countries where the cost of implementation might hinder its adoption, edge AI-based agriculture needs to be implemented within national/regional agricultural extension services. This requires developing recommendations that optimize the production and environmental cost benefits in small-scale production systems. As the potential benefits of edge AI in agriculture make it a promising area for development and implementation, mutualizing AI equipment in farmers' communities and coordination with agricultural extension offices are potential ways to share the costs, increase efficiency and create communities of expert users. Edge AI will not only improve agricultural production and profit but also substantially contribute to sustainable environmental stewardship and associated ecological benefits.

Achieving the full potential of edge AI

While edge AI-supported agriculture holds great promise for sustainable agriculture and enhanced efficiency, a comprehensive assessment of its implications within the sustainability framework is imperative. To foster the development and deployment of edge AI-based solutions in agriculture, three key tensions must be addressed: striking a balance between edge AI innovation and equitable resource distribution, promoting inter- and intra-generational justice, and aligning environmental, social and economic priorities. As we chart our course towards a technologically advanced future in agriculture, it is of paramount importance that we avoid disregarding the ecological and social dimensions that are integral to sustainable development. This necessitates a transdisciplinary endeavour to effectively address the challenges and capitalize on the opportunities presented by edge AI. By embracing such an approach, we can genuinely ensure that edge AI contributes to a sustainable and profitable agriculture, fostering benefits for farmers, the environment, ecosystems and society at large. These considerations lay the foundation for a harmonious integration of advanced technologies into our diverse global agricultural systems and societies.

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The authors declare no competing interests.

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