Digital Agriculture for the Years to Come

P. M. Priyadarshan, Suprasanna Penna, Shri Mohan Jain, and Jameel M. Al-Khayri

Abstract The agriculture industry has evolved significantly over the last 50 years. Technology developments have led to larger, quicker, and more productive farm equipment, enabling the more efficient cultivation of larger areas. Additionally, improved irrigation, fertilizers, and seed have helped farmers to increase crops. New technologies such as artificial intelligence, analytics, networked sensors, and others may increase yields even further, improve the efficiency of water and other inputs, and promote sustainability and resilience in cattle rearing and agricultural output. Implementing such cutting-edge technologies is known as agriculture 4.0. But, without a solid infrastructure for connectivity, none of this is practical. If connection is successfully implemented in the industry, agriculture may add $500 billion in value to the global GDP by 2030. This would lead to an increase of 7–9% over the anticipated total and greatly relieve the pressure currently imposed on farmers. It is one of just seven industries that will raise global GDP by $2 to $3 trillion over the next 10 years because of better connectivity. World population is expected to grow to 9.6 billion by 2050 that lead to significant increase in the demand for food. On the other hand, the availability of natural resources like freshwater and productive arable land is getting constrained year after year. Nearly 821 million people still suffer from hunger. Digital agriculture, also known as smart farming or e-agriculture, is the use of tools to collect, store, analyze, and disseminate electronic data and/or information in agriculture.

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The present emphasis is on reducing water, energy, and material use in agriculture as access to water and material resources becomes more challenging due to climate change and population expansion. Controlled environment agriculture (CEA) can be used to grow vegetables and high-value commodities in any environment with outstanding water, soil, and fertilizer efficiency, since local production reduces transportation costs. Contrary to conventional field agriculture, CEA offers more effective nutrient usage while using up to 80% less land and nearly 90% less water. Keeping in view of the population progression, declining land resources, and climate vagaries, there is a need to develop selection methods with more accuracy and precision. The advancement of artificial intelligence (AI) in the past decade has offered great potential to augment the climate smart agriculture. Protected agriculture, as against open-field farming, offers a more conducive and manageable environment for crop growth through greenhouse technology, which is somewhat unrestricted by the natural environment and encourages the intensive and effective use of agricultural resources. Remote sensing (RS) is a diagnostic tool that can act as an early warning system. Due to recent developments in sensor technologies, data management, and data analytics, the agricultural community now has access to a number of RS choices. All digital technologies that can be used in agriculture to improve yield, plant protection and enhance nutritional quality are summarized here.

Keywords Digital agriculture · Vertical farming · Controlled environment agriculture · Sensors · IoT · Big data · Block chain · Supply chain · Robotics · Remote sensing

1 Introduction

The agriculture industry has changed significantly over the last 50 years. Technology developments have led to larger, quicker, and more productive farm equipment, enabling the more efficient cultivation of larger areas. Additionally, improved irrigation, fertilizers, and seed have helped farmers to increase crops. A new revolution in agriculture is currently taking place, one that is being fueled by connectivity and data (Mehrabi et al. 2021; Himesh et al. 2018). New technologies, such as artificial intelligence, analytics, networked sensors, and others, may increase yields even further, improve the efficiency of water and other inputs, and promote sustainability and resilience in cattle rearing and agricultural output (Javaid et al. 2022). Implementing such cutting-edge technologies is known as agriculture 4.0. (da Silveira and Amaral 2022). But, without a solid infrastructure for connectivity, none of this is practical. If connection is successfully implemented in the industry, agriculture may add $500 billion in value to the global GDP by 2030. This would lead to an increase of 7–9% over the anticipated total and greatly relieve the pressure currently imposed on farmers. It is one of just seven industries that will raise global GDP by $2 to $3 trillion over the next 10 years because of better connectivity (Goedde et al. 2020).

World agriculture is facing multiple challenges. World population is expected to grow to 9.6 billion by 2050 that lead to significant increase in the demand for food (Trendov et al. 2019). On the other hand, the availability of natural resources like freshwater and productive arable land is getting constrained year after year. Nearly 821 million people still suffer from hunger (FAO 2018). The agri-food sector remains critical for livelihoods. There are more than 570 million smallholder farms worldwide (Lowder et al. 2016). As per ILOSTAT, agriculture and food production accounts for 28% of the entire global workforce (ILOSTAT 2019). If the UN Sustainable Development Goal of "world with zero hunger" by 2030 has to be achieved, then more productive, efficient, sustainable, inclusive, transparent, and resilient food systems are prerequisites (FAO 2017). This calls for urgent transformations in the agri-food system.

By 2030, the world's water supply won't be able to meet the demand, and rising costs for energy, labor, and nutrients are already placing pressure on profit margins. Before it can support large-scale agriculture once more, a fifth of the world's arable land needs to be repaired extensively. The need for more ethical and sustainable agricultural practices, such as stricter guidelines for farm animal care and reduced chemical and water use, is also being pushed by mounting societal and environmental concerns. Environmental challenges include global warming and the financial toll of extreme weather (Ebi et al. 2021). It is under such circumstances the digital agriculture stems promise (Lajoie-O'Malley et al. 2020).

Digital agriculture, also known as smart farming or e-agriculture, is the use of tools to collect, store, analyze, and disseminate electronic data and/or information in agriculture (Shepherd et al. 2018). Digital technologies are being quickly incorporated into agriculture. Big technology companies, small local enterprises, and governments are designing and funding a variety of solutions aimed at creating the "smart" farmer, from self-driving tractors to soil disease-detecting drones, from milking robots to farm management apps (Pauschinger and Klauser 2022). The use of "smart" technologies (Chugh et al. 2021) and "big data" (Protopop and Shanoyan 2016) as software-driven systems in agricultural production sites is sometimes referred to as "smart farming."

1.1 Facets of Digital Agriculture

Over the years, international agriculture experienced three main stages: primitive agriculture stage, traditional agriculture stage, and modern agriculture stage. Primitive agriculture undertook easy work by stoneware. Traditional agriculture stage produced tools made of iron and wood. During modern agriculture, advanced machines are used wherein agricultural economy ushered new heights. Current agriculture realizes information through digitalization. Digital agriculture is agriculture driven by digits. It integrates data collection, data transmission, data processing, digital control machinery, network, and automation (Bacco et al. 2019; Ingram and Mayne 2020). These processes are coordinated by cloud computing with its arms like breeding informatics, analytics, mobile services, digital services, GIS, UAVs, and Internet of things (IoT) (Fig. 1). By definition, digital agriculture (DA) is the integration of new and advanced technologies to enrich the farmer and other stakeholders within the agriculture value chain to enhance food production. Today the term "agricultural digitalization" refers to the process of integrating advanced digital technologies like artificial intelligence, big data, robotics, unmanned aviation systems, sensors, and communication net-works, all connected through the Internet of Things into the farm production system (Lioutas et al. 2021; MacPherson et al. 2022).

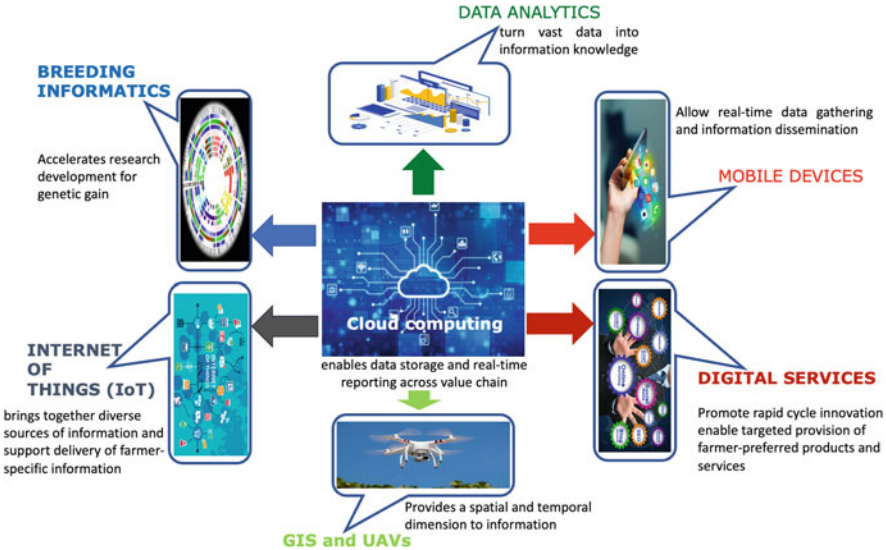

Fig. 1 Various facets of DA. Cloud computing is the delivery of computing services – including servers, storage, databases, networking, software, analytics, and intelligence over the Internet ("the cloud") to offer faster innovation, flexible resources, and economies of scale. Breeding bioinformatics: A modern breeding program with advanced phenotyping and genotyping technologies has the potential to create vast amounts of data. Breeding bioinformatics manages and converts this data into valuable information in a time-sensitive manner. Data analytics: is the process of exploring and analyzing large datasets to find hidden patterns, unseen trends, discover correlations, and derive valuable insights to make predictions. It improves the speed and efficiency of your agriculture. Mobile devices (smart phones): is equipped with various sensors are opening new opportunities for rural farmers who previously had limited access to up-to-date agricultural information like market, weather, and crop disease news. Digital services: refers to the electronic transfer of information including data and content across numerous platforms and devices like web or mobile. Geographic information system (GIS): is a computer system that analyzes and displays geographically referenced information. It uses data that is attached to a unique location. GIS is being merged with unmanned aerial vehicles (UAVs) to plan, construct, and implement various agricultural practices. The Internet of Things (IoT): describes the network of physical objects ("things") that are embedded with sensors, software, and other technologies for the purpose of connecting and exchanging data with other devices and systems over the Internet

The world's agri-food system is increasingly subject to constraints, especially since it relies on a number of nonrenewable resources that are becoming scarcer (fresh water, phosphorus, oil, cultivable soil, etc.). This system will soon exert its impact over climate change, both directly (extreme weather events, drought, etc.) and indirectly (melting glaciers, proliferation and spread of harmful species of organisms and diseases, rising sea levels) (UNESCO 2019). The collapse of biodiversity in seeds, pollinators, crop auxiliaries, etc. are looming large that endangers many ecosystems (FAO 2019a, b). Conflicts over the use of land and water will also increase with the use of biomass for energy and the implementation of afforestation/reforestation programs to capture CO_2. This is also known as "negative emissions" technique that now substantiates all IPCC scenarios limiting the temperature increase to 2 °C. In addition, the yield of cereals deemed critical for food security as their yields seem to have reached a plateau (Maurel et al. 2022) (see Iddio et al. 2019 for a comprehensive review).

In many parts of the world, climate change has caused many irregular and extreme weather events (Li et al. 2021). Different parts of the world have begun experiencing intense drought, hurricanes and storms, and floods as a result of global warming (FAO 2021). Additionally, agricultural production success varies based on the complex environmental effects of global warming and climate change, both in the short and long term (Hatfield et al. 2011). Extreme heat, extreme cold, wetness, and dryness all have a deleterious impact on plants (Hatfield and Prueger 2015; FAO 2019a, b). Trade conflicts, epidemic and vegetative diseases, rising seed and fertilizer prices and wages, flash floods, heatwaves, and other weather variations all have a negative impact on agriculture. However, as evidenced by agriculture's contributions to greenhouse gas emissions, water pollution, and biodiversity loss (Springmann et al. 2018), major agricultural systems are on largely unsustainable trajectories. Countries must create policies and programs in a sustainable manner if they are to overcome these obstacles and satisfy future demands. The best ways to achieve sustainable agricultural development are to continue the process of innovation using contemporary genetic and information technologies to increase agricultural productivity while balancing economic, environmental, and social outcomes related to food and agricultural systems (Basso and Antle 2020).

Industrial agriculture has a substantial negative impact on the ecosystem as a result of human activity, which today controls almost all biogeochemical cycles on Earth (Park et al. 2016). Production from industrial agriculture is expected to rise by 100–110% between 2005 and 2030, which calls for substantial inputs of finite resources like fresh water, soil with sufficient sunlight, and nonrenewable nutrients (e.g., phosphorus) (Cordell et al. 2012). The degradation of soils, aquifer depletion, saltwater-intrusion, runoff and eutrophication, and emissions (e.g., CO_2, N_2O, etc.), contributing to global warming and resource scarcity are all effects of modern intensive agriculture (Cohen et al. 2022). In particular, this is because farmers frequently lack sufficient measuring, modeling, and dynamic control mechanisms to optimize inputs for plant growth (Dawson and Hilton 2011). Moreover, losses from farm to fork in the form of food waste can reach as high as 40% due to extended supply chains (Cohen et al. 2022).

The present emphasis is on reducing water, energy, and material use in agriculture as access to water and material resources becomes more challenging due to climate change and population expansion (Cohen et al. 2022). Regional decentralized controlled environment agriculture is one suggestion for enhancing the sustainability of vegetable production. The benefit of this is that practitioners can precisely control environmental effects, including nutrient application, water use efficiency, and lighting. Hydroponics or soilless culture feeds nutrients and water directly to the plant by employing recirculation (where the substrate is reused in the system until the nutrients are exhausted) or flow-through substrates (Silberbush et al. 2005). Controlled environment agriculture (CEA) can be used to grow vegetables and high-value commodities in any environment with outstanding water, soil, and fertilizer efficiency, since local production reduces transportation costs (Van Ginkel et al. 2017). Contrary to conventional field agriculture, CEA offers more effective nutrient usage while using up to 80% less land and nearly 90% less water (Carmassi et al. 2007).

In order to manage soil, climate, and genetic resources at the field and landscape scales, digital agriculture uses a collection of geospatial and digital information technologies that integrate sensors, analytics, and automation (Basso and Antle 2020). Big data, the Internet of Things (IoT), augmented reality, robotics, sensors, 3D printing, system integration, ubiquitous connectivity, artificial intelligence, machine learning, digital twins, and blockchain are just a few of the technologies that make up digitalization (Alm et al. 2016) (Table 1), which is anticipated to fundamentally alter daily life (Klerkx et al. 2019, food, fiber, and bioenergy supply chains and systems) and agricultural productivity processes. According to Rotz et al. (2019), the early indications of transition are already apparent.

Several concepts have emerged with digitalization in agricultural production systems, value chains and more broadly food systems. These include *smart farming, precision agriculture* or *precision farming, decision agriculture, digital agriculture*, *agriculture 4.0,* or what is referred to in French as *Agriculture Numérique* (i.e., *numerical agriculture*) (Rose and Chilvers 2018; Klerkx et al. 2019). On-farm management duties that take into account location, weather, behavior, phytosanitary status, consumption, energy use, prices, and economic data are all included in digitalization. This is done with the aid of sensors, equipment, drones, and satellites. Through ongoing monitoring or targeted big data science inquiries, the data so acquired is then utilized to understand the past, anticipate the future, and make more timely or correct judgments (Ingram and Maye 2020). These developments have mostly concentrated on deploying technologies for enhancing post-farmgate operations, postharvest quality monitoring, and real-time traceability (Rutten et al. 2013; Wolfert et al. 2017). This claim is supported by a variety of reviews on subjects such precision farming, big data analysis, drones, artificial intelligence, robots, 3D printing, and the Internet of Things (IoT), as well as their potential to enhance agricultural production systems, value chains, and food systems (Bertoglio et al. 2021). For instance, yield stability maps show regions that have consistently high production throughout time, regions with poor productivity, and other regions

Table 1 Technologies used in digital agriculture

Robotics	Agricultural robots are for increasing production yields. From drones to autonomous tractors to robotic arms, the technology is being deployed in creative and innovative applications. Some of the most common robots are the following: harvesting and picking, weed control, autonomous mowing, pruning, seeding, spraying and thinning, phenotyping, sorting and packing, and utility platforms. Robots can achieve to improve the size of yields and reduce waste from crops being left in the field
IoT and sensors	The Internet of Things is utility of Internet for various operational purposes. IoT becomes operational through sensors. Sensors are devices that detect and respond to changes in an environment. Inputs can come from a variety of sources such as light, temperature, motion, and pressure. Sensors provide valuable information through a network, and they can share data with other managerial information systems. The sensor attains a physical parameter and converts it into a signal suitable for processing (e.g., electrical, mechanical, optical). The output of the sensor is a signal which is converted to a human-readable form, like changes in characteristics, changes in resistance, capacitance, impedance, etc.
Artificial intelligence (AI)	In contrast to the intelligence exhibited by humans or other animals, artificial intelligence (AI) refers to the perception, synthesis, and inference of information made by computers. The term "intelligence" refers to the capacity for knowledge, reasoning, abstraction, and inference of meaning
Deep learning (DL)	It is simply a neural network with three or more layers and is a subset of machine learning. These neural networks make an effort to mimic how the human brain functions; however, they fall far short of being able to match it, enabling it to "learn" from vast volumes of data. Additional hidden layers can help to optimize and refine for accuracy even if a neural network with only one layer can still make approximation predictions
Drones and satellites	While drones record data in real time, they lack the hard drives necessary to store the vast amounts of digital data that satellites are designed to hold until they can be recovered and used. In order to provide more accurate measurements on a particular location, drones can also use GPS
Extended reality and the metaverse	Extended reality (XR) enables users to constantly access internet content thanks to the metaverse, which also makes considerable use of 3D visuals. From augmented reality (AR) to mixed reality (MR) to virtual reality (VR), XR technologies cover a broad range of immersive technologies
Virtual reality (VR)	With images and things that seem real, a virtual reality (VR) environment gives the user the impression that they are completely engrossed in their surroundings. A virtual reality headset, helmet, or other equipment is used to view this environment
Block chain	A blockchain is a type of distributed database or ledger – one of today's top tech trends – which means the power to update a blockchain is distributed between the nodes, or participants, of a public or private computer network. This is known as distributed ledger technology, or DLT
Data analytics	Analyzing data collections to identify trends and make judgments about the information they contain is known as data analytics (DA). Data analytics is increasingly carried out with the use of specialized hardware and software
Cloud connectivity	The capacity to connect two resources within a cloud, across clouds, and with on-premises data centers is referred to as cloud networking. A cloud service provider must offer the following three main forms of connectivity: site-to-cloud, the connection between cloud resources, and on-premises hardware

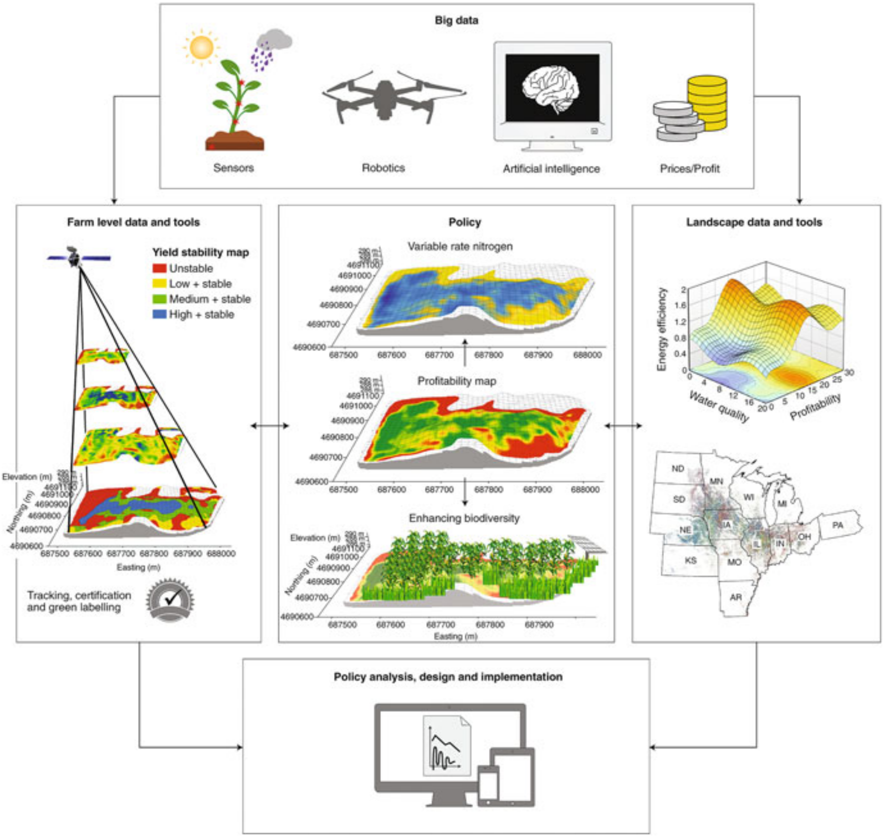

Fig. 2 DA in agricultural systems. DA can be used to design and implement sustainable agricultural systems at farm and landscape scales. With the use of stability maps, DA can help redesign fields or subareas within fields that are unprofitable or environmentally unsustainable and sustainably intensify high-yield areas of the field knowing that these can respond to more inputs. (Courtesy: Bruno Basso, Michigan State University; Nature Sustainability, doi: https://doi.org/10.1038/s41893-020-0510-0)

that have yields that fluctuate over time. Stability maps can be used by DA to redesign unprofitable or environmentally unsustainable fields or portions of fields, as well as sustainably intensify culture in high-yield regions that respond to more inputs (Fig. 2).

1.2 *Controlled Environment Agriculture (CEA)*

Controlled-environment agriculture (CEA), which deals with sophisticated horticultural practices and technological advancements, first gained popularity in the 1960s

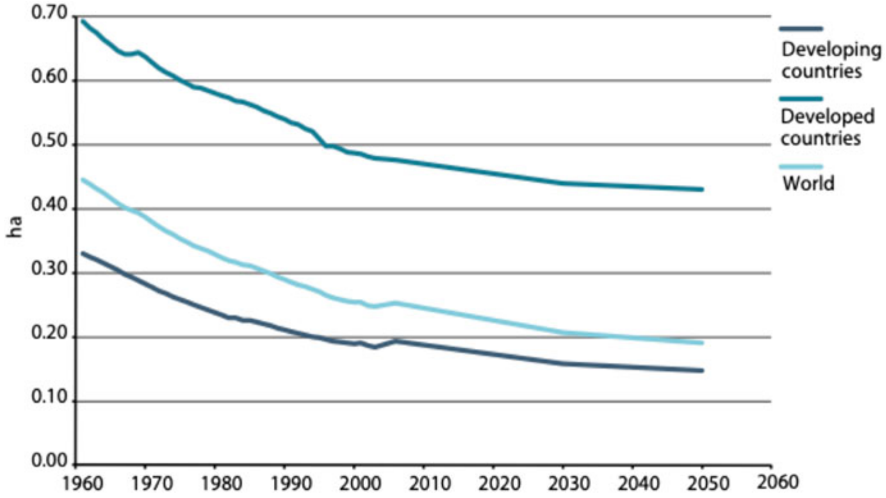

Fig. 3 Arable land per capita from 1960 to 2050. (FAO 2011)

(Hodges et al. 1968). Controlled environments (CEs) promote production efficiency, optimize plant yield, and enhance product quality by providing predictions on how plants will appear in their surroundings. The market has recently seen a rise in demand for locally sourced food. According to Eaves and Eaves (2018), this is accomplished through CEA, which covers small- (in-home production or indoor gardens), medium- (community gardens), or large-scale commercial operations. The ability to alter production environments to increase plant quality and output, lengthen growing seasons, and allow crop production under unfavorable climatic conditions (e.g., wind, rain, extremely high temperatures, and inadequate light) is a fundamental advantage of CEA. The two most prevalent types of CEs used in urban agriculture (UA) are greenhouses and plant factories (PFs). Due to the decreasing amount of arable land, such systems are unavoidable (Fig. 3). Controlling greenhouses presents a particular difficulty, because it calls for systems that can adapt to the microclimatic factors and constantly shifting environmental circumstances. The expense of heating and cooling greenhouses can account for 70–85% of the overall operating cost in northern latitudes and harsh climates (Engler and Krarti 2021).

1.2.1 CEA Facilities

All CEA facilities are included under the general term “urban agriculture” (UA). CEA, on the other hand, is merely a portion of UA as a whole that has conditioned spaces. There are many different kinds of CEA facilities, including greenhouses, plant factories, rooftop gardens, and vertical farms. The market for indoor farming was estimated to be worth 38.7 billion USD in 2022 and may rise to 96.6 billion by 2032. The market share now owned by Europe is the greatest, but due to their geographic constraints and economic development, India, China, Mexico, and Singapore are experiencing significant expansion (Specht et al. 2013). At the moment, greenhouses hold 70% of the market. The common CEAs include vertical farms, rooftop gardens, planned factories with artificial lighting, hydroponics, and aquaponics.

Scissor lifts, ladders, stairs, or stacked A-frames are frequently used in vertical farms (VFs) to raise crops vertically (Beacham 2019). In comparison to traditional farming, VFs can stack these plant beds to boost agricultural yields by 10–100 times (Fig. 4). The annual growth of VFs is so exacting that it reported using almost twice as much water as traditional farming (Tong et al. 2016) while growing at a rate that was nearly two times as fast. Building rooftop gardens (RTGs) requires minimal to no structural upgrades. RTGs are marketed as energy-efficient building components, because they can lower both the winter and summer heating and cooling loads. If implemented on a number of buildings, greening the roofs could also aid in reducing the impacts of urban heat islands (Fig. 5).

The advantages of RTGs are used in many building integrated agriculture (BIA) applications to produce energy-efficient CEAs (Benis et al. 2017; van Delden et al. 2021). Artificial lighting plant factories (PFALs) are often referred to as closed plant production systems (CPPS), which are totally sealed off from the outside

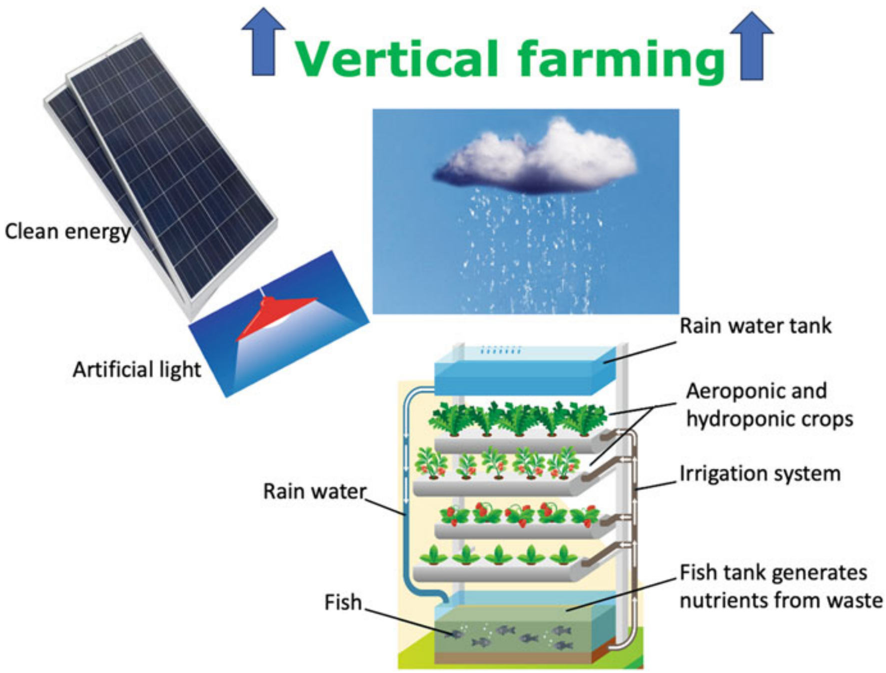

Fig. 4 Vertical farming

Fig. 5 RTGs (rooftop garden)

Fig. 6 Hydroponics

(Kozai 2019). They are often built in a building that resembles an airtight warehouse, with rows of tall, stacked plant beds that are illuminated artificially. Comparing the profitability of growing leafy vegetables in a greenhouse with a PFAL, the latter has an internal rate of return that can reach 35% (Eaves and Eaves 2018; Avgoustaki and Xydis 2020). There is some crossover between different CEA facilities, as a completely insulated VF or RTG could also be considered to be a PFAL (Zhuang et al. 2022).

Hydroponic crop cultivation has a number of potential advantages, including as separation from soil- or water-borne problems (such as nematodes, salinity, or heavy metals). Control over water and nutrient uptake has improved. The topic has received positive reviews (Raviv et al. 2019; Jones Jr 2014). Crops grown utilizing soilless culture are frequently cultivated in troughs, bags, or containers to facilitate effective management of the root zone (Fig. 6). In their list of typical nutrient sources for soilless cultivation, Raviv et al. (2019) mention raw irrigation water, fertilizers that are frequently incorporated into a substrate, substrate components, and a provision to modify the pH of the substrate. A thorough description of management techniques for soilless culture systems is given by Nelson (2012).

Nutrient-film technique (NFT), deep-water culture (DWC; also known as deep-flow method, raft, raceway, or floating hydroponics, among other names), and aggregate culture are hydroponic systems that are frequently employed in UA (Gómez et al. 2019). Crops grown in slanted troughs with a thin film of nutrient solution flowing over the roots (either constantly or sporadically) constitute NFT. Roots are continuously submerged in a nutritional solution in DWC systems. In aggregate culture, crops are grown in containers or on substrates that have been bagged, with drip systems used to apply nutritional solutions. For leafy greens and herbs, NFT and DWC systems are frequently employed. Aggregate culture is recommended for long-term fruiting crops including strawberry (*Fragaria x ananassa*), cucumber (*Cucumis sativus*), sweet pepper (*Capsicum annuum*), and tomato (*Lycopersicon esculentum*) (Gómez et al. 2019).

For soilless culture, substrate selection is a critical. Primary substrate components consists of >40% of the substrate volume. They are organic materials with low bulk density and high water-holding capacity like peatmoss and coconut coir fiber (Argo and Fisher 2002; Gómez et al. 2019). On the other hand, secondary components that consist of <40% substrate volume include expanded minerals like perlite, vermiculite, clays, sand, and composts that increase drainage and cation exchange capacity to increase aeration and nutrient retention (see Raviv et al. 2019 for a review).

1.2.2 Optimal Growth Conditions

The CEA sector struggles to attain economic viability due to ineffective microclimate and rootzone-environment management and excessive prices. Microclimate control, comprising light, temperature, ventilation, CO_2, and humidity, is crucial for producing uniform, high-quantity, and high-quality crops (Ojo and Zahid 2022). The focus of the most recent 10 years' research has been on the establishment of intelligent systems in CEA facilities, such as nutrient solution management for hydroponic farms and cloud-based microenvironment monitoring and control systems (Michael et al. 2021). According to Monteiro et al. (2018), artificial intelligence (AI) algorithms have also opened up new possibilities for intelligent predictions and self-learning. A subset of machine learning called deep learning (DL), which has a large presence in many contemporary technologies, has attracted a lot of interest in recent years.

In order to automate watering in vertical stack farms and microclimate control, computer vision and deep learning algorithms have been used (Ruscio et al. 2019). This has made it easier for growers to carry out quantitative assessments for high-level decision-making. A tiny indoor farm of less than 1500 ft^2 requires three personnel to complete manual CEA, which is labor-intensive. However, intelligent automation may be able to overcome these issues employing optical sensors coupled with DL-based prediction models (Namuduri et al. 2020). Several sensors, including cameras and LiDAR, are used to detect targets (Mendez et al. 2021).

1.2.3 Optimal Growth Environment and Automation

The crop quality and yield can be impacted by a number of indoor circumstances (Gibson 2018; Engler and Krarti 2021). The reported literature indicates four primary elements as being essential to creating ideal indoor growing settings:

- Temperature
- Humidity and transpiration
- Chemical balances
- Photosynthetic photon flux (PPF)

Temperature Temperature influences the timing of plant growth events such as maturation, flowering, and fruiting, and seeding is temperature-influenced in most plants (Kozai et al. 2019). For example, warmer temperatures speed up the process until flowering occurs at ideal levels. Below this threshold temperature, flowering progresses slowly and eventually stops completely at the ceiling temperature (Engler and Krarti 2021). Stressing plants at the end of their life is standard procedure for all flowering and fruiting plants. Stresses are modulated to mimic the challenges that plants face in the wild before they die, including imposing drought conditions, reducing temperature and nitrogen levels. Graamans et al. (2018) estimated the growth rate of lettuce and found that the optimum temperature for photosynthesis is between 20 and 25 °C, the optimum for respiration is between 30 and 35 °C, and the optimum dry matter production is between 16 and 17 °C (Graamans et al. 2018). LEDs are commonly used in CEA applications. It emits far less far-infrared radiation and is more energy efficient than traditional high-pressure sodium lamps used in greenhouses. Therefore, LEDs can help keep plants at the right temperature (Kozai et al. 2019).

Humidity and Transpiration Plant transpiration is hampered by the high relative humidity at the CEA facility. Vapor pressure deficit (VPD) is used to determine how much water can be contained in the air around a leaf, depending on its surface characteristics and a given temperature. The ideal VPD range for many plants is between 0.8 kPa and 0.95 kPa (Kozai et al. 2019). Reduced VPD prevents transpiration, which leads to water storage by the plant, promotes the growth of fungus, and finally reduces output (Linker et al. 2011). Yet, higher VPD needs higher water consumption, potential loads, and heating, ventilation, and air conditioning (HVAC) requirements. Plant stomata have the capacity to completely close, stopping transpiration (Engler and Krarti 2021). Stomata, which are openings in the plant wall, are used for respiration. Stomata can detect changes in light, temperature, humidity, and CO_2 concentration. The amount of water transpired is influenced by the root-shoot ratio, VPD, leaf area, and surface characteristics (Kozai et al. 2019; Bramley et al. 2022). Deep roots enable a plant to store more water for transpiration by the shoot. In plants, larger leaves often absorb more water than smaller leaves. Plants with thick cuticles, thick cell walls, sunken stomata, or hairs can reduce the rate of transpiration in order to raise the boundary layer between the stomata and the sensible heat of the flowing air (Passioura and Angus 2010). It is assured that CO_2 and water vapor will diffuse into the plant's leaves by maintaining a horizontal airflow rate of 0.3–0.5 m/s. The ideal airflow for some plants, such as tomato seedlings, is 0.7 m/s, but generally speaking, airflows up to 1.0 m/s can unduly stress the plant. Additionally, natural convection caused by ventilation can stop overheating in the top rows of a CEA plant (Kozai et al. 2019).

Chemical Balances Improved rates of nutrient intake, photosynthetic assimilation, and product nutritional value are all strongly associated with CO_2 enrichment (Vanhove et al. 2011). Due to cost constraints, persistently gloomy weather, or high ventilation rates in hot regions, CO_2 enrichment might only be practical for a small number of CEA sites (Li et al. 2018a, b). The production of biomass and amino acids in lettuce is said to be enhanced by a CO_2 concentration of 1000 ppm, monochromatic LED, and appropriate nutrient distribution (Miyagi et al. 2017). Increasing nitrogen concentrations in recirculating hydroponic systems from 100 mg/L to 400 mg/L increases lettuce yields by 0.8 kg m^{-2} in the fall, 2.6 kg m^{-2} in the winter, and 2.3 kg m^{-2} in the spring (Djidonou and Leskovar 2019). For CEA facilities, tracer gases are utilized to measure air exchange rates. N_2O or SF_6 are frequently utilized tracer gases in construction sites and CEA facilities. Moreover, CO_2 cannot be utilized in CEA facilities, since it can be absorbed by plants, despite the fact that it is employed as a tracer gas in other sectors. These gases' resulting energy balance can be used to forecast the right ventilation rates, which would save operational expenses. The use of H_2O as a tracer gas is now the subject of research (Engler and Krarti 2021).

Photosynthetic Photon Flux (PPF) The photoperiod, or duration of the night, which characterizes the growth season for a specific latitude, determines flowering. While exposed to light, plants absorb CO_2; when it is dark, they retain it. The level of CO_2 within a CEA facility is impacted by this pattern naturally (Li et al. 2018a, b). For a number of reasons, LEDs are preferable to incandescent, fluorescent, and HID bulbs. According to Graamans et al. (2018), LEDs installed in plant factories are often set at 52%, with the remaining 48% of power being distributed as sensible heat to aid in plants' evapotranspiration. The suggested growing parameters for CEA facilities are available Table 2**.**

Automation Automation in CEA or protected agriculture can be achieved through the implementation of the Internet of Things (IoT) (Shi et al. 2019a, b). A network of physical items that are equipped with sensors, software, and other technologies is known as the Internet of Things (IoT). These "things" are able to share real-time data with other linked devices and systems through networks because they are connected to the Internet.

Table 2 Ideal indoor conditions for different crops

Crop	Temperature (°C)	RH	VPD	Lighting density	photoperiod	CO_2 concentration	Cultivation period (days)
Lettuce	25 °C (day); 22 °C (night)	60–70%	0.85–0.95	200 PPF	16 h	800–1200 ppm	30
Tomato	25–31 °C	75–85% vegetative; 65–75% for flowering	0.65–0.8 vegetative; 0.85–1.0 flowering	900 PPF	12 h	1000 ppm	90
Herbs	20 °C (day); 15 °C (night)	70–80%	0.6 (day); 0.45 (night)	67% re at 620 nm; 33% blue light at 450 nm	12 h	800–1200 ppm	50–90 depending on variety
Micro-greens	21 °C (day); 17 °C (night)	80%	0.5 (day); 0.39 (night0	85% red, 15% blue; 300–600 PPF depending on variety	16 h	500–800 ppm	7–21 depending on variety
Shiitake mushrooms	12.8–24 °C	85% early on. Can drop to 60% after 3 days of pinning, 80% is ideal	0.6–0.8	55–100 PPF	12 h	800 ppm (6–10 air changes per hours to keep CO_2 levels low)	50–60
Cannabis	22–30 °C	65–75% vegetative; 60–70% flowering; 55–65% stressing	0.80–0.95 vegetative; 1.0–1.15 flowering; 1.16–1.35 stressing; 0.65 (day); 0.45 (night0	400–600 PPF	18 h veg; 12 h flowering	800–1100 ppm	70–80
Cucumbers	21–25 °C (day); 20 °C (night)	75–80%	0.65 (day); 0.45 (night)	100 PPF early stages; 250 PPF mature; 85% red, 15% blue	16 h	450–600 ppm	55–65
Peppers	21 °C (day); 17 °C (night);16 °C (flowering)	55–65%	3–5 seeding; 1.0 (day); 0.75 (night 0 vegetative; 1.0 (day); 0.0 (night)	430–500 PPF	18 h seed; 14 h veg	450–500 ppm	50–65

Crop	Temperature (°C)	RH	VPD	Lighting density	photoperiod	CO_2 concentration	Cultivation period (days)
Strawberries	30 °C (day); 15 °C night)	65% (day); 100% (night)	1.0 (day); 0.0 (night)	300 PPF	16 h	1000 ppm	90
Blueberry transplants	23 °C average	90%	0.28	100–200 PPF	16 h	1500 ppm	30–40
Rice	23–27 °C	70%	1.05 (day); 0.85 (night)	800 PPF	12 h	400 ppm	100

Adopted from: Engler and Krarti (2021). doi: https://doi.org/10.1016/j.rser.2021.110786

With the development of agricultural sensor, wireless communication, cloud computing, machine learning, and big data technologies, IoT technology has grown and is progressively being promoted and used in the field of protected agriculture (Kamilaris and Prenafeta-Boldú 2018). It is playing an important role in many areas of protected agriculture due to its capacity to help farmers check soil quality, climatic change, and the health of animals and plants (Shi et al. 2019a, b). In the event that environmental variables alter above the predetermined threshold, IoT will automatically send an alert message to the administrator demanding that the hidden threat be eliminated. Additionally, according to Liu et al. (2018), it has the capacity to alter environmental factors like temperature, humidity, carbon dioxide concentration, and illumination in real time.

Additionally, the IoT system's cameras can capture crop diseases and insect pests in the greenhouse in real time, helping farmers to spot problems and put preventative measures into place (Ma et al. 2015). GPS, radio frequency identification (RFID), and other location-based sensors enable tracking and visual monitoring of produce during storage and transportation. Supermarket managers use their computer or smartphone to monitor and forecast product status and demand in order to get things on the shelves. Users and customers can obtain details on the variety, origin, processing, and other features of agricultural products by utilizing a QR code, barcode, etc. With the use of IoT for protected agriculture, a rural community may be constructed that is knowledgeable, connected, advanced, and adaptable. Cheap embedded devices can improve how people engage with the physical world. For further information on IoT, read the section on technology in DA. Big data, cloud computing, and edge computing can all provide insightful analysis and information that can be used to make decisions (Shi et al. 2019a, b; Quy et al. 2022).

1.3 Challenges Facing Food Production and Food Supply Chain

The food sector is crucial in providing the fundamentals and needs to support a range of human behaviors and activities (Cooper and Ellram 1993). In order for the food to reach the ultimate consumers by the due date, it must be stored, delivered, and retailed after it has been produced or harvested. According to reports, around 1.3 billion tons (or about one-third) of the food produced each year is abandoned or wasted (Manning et al. 2006). Around 1 billion tons of food are wasted each year, with two-thirds of that occurring in the supply chain during harvest, shipping, and storage (Fritz and Schiefer 2008). Consider fruit and vegetables as an example. Due to inefficient and ineffective food supply chain management (FSCM), 492 million tons of such perishable food were wasted globally in 2011 (Gustavsson et al. 2011). FSCM is important to save our food as a result (see Zhong et al. 2017 for a review).

The food supply chain has quickly evolved in recent decades, spreading internationally and engaging many more partners, making the supply chain longer and more sophisticated than before. Today's consumers expect exotic delicacies, fresh on their plates, year-round. As if things weren't already challenging enough, the multiyear COVID pandemic shutdown in 2020 put even more strain on supply chains by closing down numerous restaurant and food service supply chains and raising the stakes for retail chains and direct-to-consumer food delivery (Huang et al. 2021).

1.3.1 Blockchain Technology

Blockchain technology, a sophisticated database system, permits open information exchange inside a business network. In a blockchain database, data is held in blocks that are linked together in a chain. The data is still constant in time, since the chain cannot be deleted or changed without network agreement. You can set up an unchangeable or immutable ledger using blockchain technology to manage orders, payments, accounts, and other transactions. The system's built-in capabilities, which also prevent unauthorized transaction submissions, make it possible to see these transactions as a whole.

1.3.2 e-Commerce Software

A stand-alone program or software suite called e-commerce software gives the ability to sell your goods and services online. The front end, which is your website, makes it simple for customers to make purchases, while the back end allows you to streamline all of your procedures from inventory to sales.

Each style of e-commerce software is available and can be customized to meet your objectives and financial constraints. Although it's not a rule, the sort of e-commerce website software you use usually depends on the size of your company. Software-as-a-Service, Platform-as-a-Service, or an on-premise platform that gives you control over the server and software used to offer your e-commerce website are all options for your e-commerce needs.

1.4 Climate Smart Agriculture

Climate change has imposed several adversaries to the planet ecosystem through erratic environmental fluctuations in temperature, rain pattern, and drought occurrence (IPCC 2018). The continuous changing scenario not only disturbs the crop growth and production but also affects the food security and the incidence of diseases (Chakraborty and Newton 2011). It has been unequivocally demonstrated that the climate change has set an impact on all the pathogen, host, and plant environment (Singh et al. 2023). Since agricultural productivity is crucially affected by plant diseases, the fluctuating climatic environment has led to different disease related modalities, such as distribution pattern, resurgence, widespread infestation, and new pathotypes (Velásquez et al. 2018). Cases like intense Ascochyta blight in chickpea occurred due to infrequent late rainfall resulting in yield and quality losses (Addisu et al. 2023), and the shift in rainfall pattern due to an El Nino event has damaged lentil crop due to rust infestation in Ethiopia (Pathak et al. 2018).

Since the dawn of agriculture, there have been technological developments, which have paved the way for improvement of crop plants and refining the crop cultivation and management. Plant breeding has witnessed genetic and agronomic interventions to enhance the pace and accuracy of plant selection (Wijerathna-Yapa and Pathirana 2022). Keeping in view of the population progression, declining land resources, and climate vagaries, there is a need to develop selection methods with more accuracy and precision. The advancement of artificial intelligence (AI) in the past decade has offered great potential to augment the climate smart agriculture. AI technology through the use of high-throughput genomics and phenomics methods can quicken the course of breeding new plant varieties (Khan et al. 2022; Harfouche et al. 2019). The machine learning tools have found their application in marker-assisted selection, genomic prediction, and genomic selection (Esposito et al. 2020; Reinoso-Peláez et al. 2022). The tools including ML, deep learning, and predictive analysis can help in the analysis of complex, huge agricultural datasets to extract useful information about traits, and their associations of plant responses to stress conditions (Tong and Nikoloski 2021; Crane-Droesch 2018). Genomic technologies together with high-throughput phenotyping provide the trait related information to researchers to guide and notify the breeding methods to adopt for climate-smart breeding (Marsh et al. 2021). AI plays a vital role in integrating and handling the huge data by conducting association studies to identify genomic targets associated with disease response traits (Khan et al. 2022). Breeders can use the data for management of crop plants for their adaption to stresses and introgression through the use of genomic selection or genome editing tools (Harfouche et al. 2019).

Plant diseases inflict severe losses on plant productivity and affect global food security. It has been demonstrated that the changing climatic factors worsen the conditions for resurgence of plant and crop diseases. This warrants the need of a greater understanding of the changing climate effects on crop plants in a spatial and temporal manner under realistic field scenario. The intervention of information technologies such as the Internet of Things (IoT), remote sensing, unmanned aerial vehicles, and artificial intelligence has revolutionized the agriculture (Gao et al. 2020). These digital technologies have been pivotal in generating huge amount of data to aid the understanding of crop breeding for several applications, such as prediction of yield, weed and pest/disease detection and forecast, risk management, food safety, and spoilage inhibition. Kreuze et al. (2022) suggested the use of image detection from smartphones or unmanned aerial vehicles for monitoring of pest and disease and data handling for modeling, predictions, and forecasting regarding climate change in root, tuber crops, and banana.

The deep learning tools have also found their place in agriculture, for weather forecast (Schultz et al. 2021). Neural networks are regularly used in the context of plant diseases, such as epidemiology or remote sensing (Zhang et al. 2005;

Selvaraj et al. 2019). In case of powdery mildew disease, UV-B light has shown good application for disease management in grapes and strawberry (Onofre et al. 2021; Meyer et al. 2021). Application of pesticides on crops like grapes can be very well done using robotics systems (Oberti et al. 2016). Disease phenotyping often plays a crucial role in field grown plants, for example, in potato in the context of potato blight, efficient phenomics-assisted screening has been used for disease resistance (Gold et al. 2020). The deep learning and machine learning are also used to precisely categorize breeding germplasm for resistance to potato late blight (Gold et al. 2020), *Rice hoja blanca virus* (Delgado et al. 2019), and banana Xanthomonas wilt (Selvaraj et al. 2020). There have been several studies indicating that it is possible to go for early, nondestructive prediction of the onset of disease based on primary symptoms such as mild and small lesions by using imaging spectroscopy (Gold 2021).

1.5 Technologies in DA

The phrase "Internet of Things" was first coined in 1999 by computer scientist Kevin Ashton. While working at Procter & Gamble, Ashton promoted the use of radio frequency identification (RFID) chips to track products as they move through a supply chain. A five-layer IoT architecture was created by Shi et al. (2019a, b) based on the realities of protected agriculture and the expertise of other academics. In Fig. 7, these levels are succinctly proposed as a five-layer system.

- Perception layer: This layer is made up of various sensors, terminal devices, farm machinery, wireless sensor networks (WSN), RFID tags and readers, etc. Common sensors include machines, wireless sensor networks (WSN), RFID tags and readers, and other objects. Common sensors include those that collect data on the environment, plants and animals and other agriculturally related sensors. These sensors can offer temperature, humidity, and wind speed data to agriculture. Data on variables, including temperature, humidity, wind speed, plant diseases, insect infestations, and animal vital signs, can all be collected with these sensors. Information has been acquired about plant diseases, insect pests, and animal vital signs. The gathered data is simply analyzed by the embedded device and uploaded to a higher layer through the network for additional processing and analysis.
- Network layer: The infrastructure of the Internet of Things is made up of a converged network that consists of the Internet and various other communication networks. The transmission medium network is made up of the Internet and other communication networks. For the transmission, the medium can be either wired technology, such as CAN bus and RS485 bus, or wireless technology, such as Bluetooth, LoRa, and NB-IoT, as well as wireless technology, such as Zigbee. Agricultural data is also transmitted across the network layer using Bluetooth, LoRa, Zigbee, and NB-IoT. The network layer not only transmits

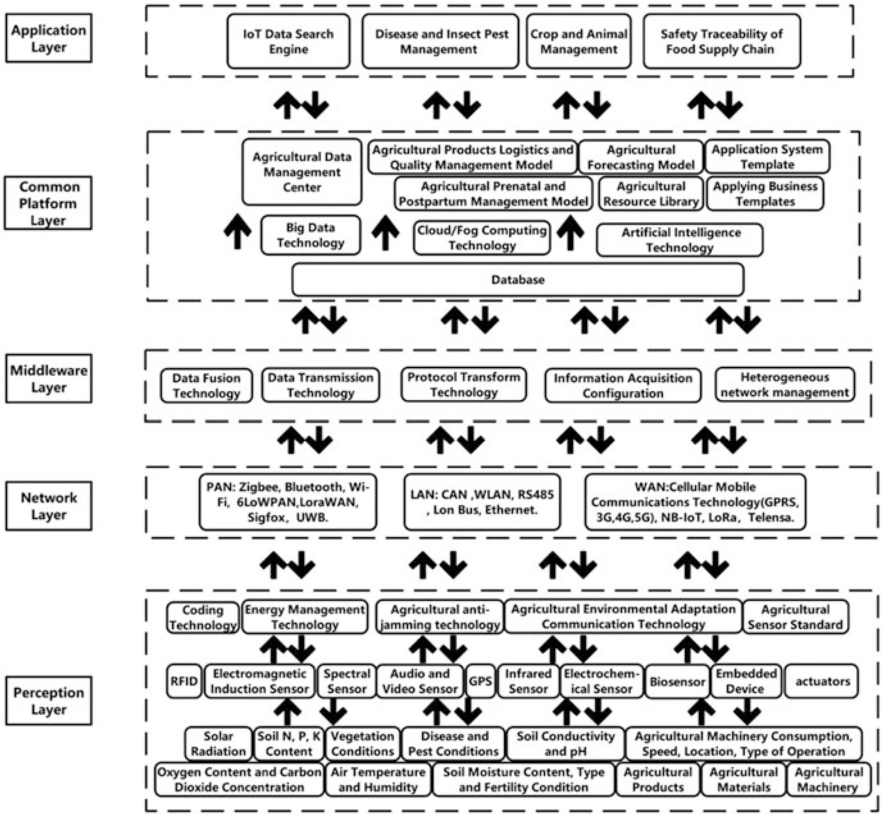

Fig. 7 Structure of IoT in protected agriculture. (After Shi et al. 2019a, b; courtesy: Sensors; doi: https://doi.org/10.3390/s19081833)

different kinds of related information gathered by the perception layer to the higher layer, but it also sends control agricultural related information gathered by the perception layer to the higher layer and commands from the application layer to the perception layer, causing the related network layer devices to act appropriately.

- Middleware layer: IoT may provide a range of services to fit a range of devices. Because each device's technical requirements (CPU, power source, communication module, and system) are unique from the others, heterogeneity issues can occur. Different devices are unable to connect to and communicate with one another as a result. The middleware layer's aggregation, filtering, and processing cause heterogeneity issues. The middleware layer collects, filters, and processes data from IoT devices, greatly lowering processing time and cost while providing developers with a more flexible tool to build their applications. It also simplifies the processes for introducing new hardware and software, facilitating its faster integration with existing systems and boosting IoT compatibility.

- Common platform layer: The organization, decision-making, summary, and statistics of agricultural data, as well as the creation of diagnostic analysis, forecasting, and early warning systems, are all responsibilities of the common platform layer. Machine learning, big data, edge computing, cloud computing, fog computing, diagnostic reasoning, and early warning and prediction are all part of this layer. An algorithm, extra commonly used core processing technologies, and its business model are all included in this layer.
- Application layer: The value and utility of the Internet of Things are most clearly seen at here, the highest level of the architecture. This layer includes a number of intelligent platforms or systems for environmental monitoring and control of plants and animals, early warning and management of diseases and insect pests, and traceability of the safety of agricultural products. These systems can all improve production efficiency and save money and time.

1.5.1 Crucial Technologies of IoT

Sensor Technology In order to collect data about the environment, plants, and animals, sensors are crucial and one of the technological barriers in the development of the Internet of Things (Shi et al. 2019a, b). Around 6000 research and production groups, including well-known companies like Honeywell, Foxboro, ENDEVCO, Bell & Howell, and Solartron, are now working on sensor research, representing more than 40 different countries. The three most often used types of agricultural sensors are physical property type sensors, biosensors, and micro-electromechanical system (MEMS) sensors. The majority of temperature, humidity, and gas sensors fall under the category of physical property sensors, which convert signals by physically altering the material's sensitivity. The biosensor (Li et al. 2018a, b) is primarily used to detect pesticide residue, heavy metal ions, antibiotic residue, and toxic gas and includes enzyme sensors (Zheng et al. 2015), microbial sensors, adaptive sensors (Jiao et al. 2018), etc. It transmits information based on the organism's reaction to the outside environment. The MEMS sensor is a standout among the most recent research and development efforts in the area of dependable, affordable, and compact sensors (Negara et al. 2014). There could be hundreds, thousands, or even millions of nodes in a sensor network. The cost of each node needs to be kept to around $1 in order for the sensor network to be practicable; however, it is now as high as $80 (Shi et al. 2019a, b).

Data Transmission Technology When compared to conventional transmission technologies like fieldbus, wireless communication technology offers advantages, including inexpensive construction and maintenance costs, low-power consumption, and great extensibility. In order to develop their WSN for environmental monitoring (Kumar and Hancke 2014), autonomous irrigation (Rajalakshmi and Mahalakshmi 2016), and remote control (Revathi and Sivakumaran 2016), the majority of scientists, enterprises, and producers currently employ it. The heterogeneity of the IoT has been slightly increased as a result of businesses and research groups developing their own wireless devices. Additionally, interference between wireless signals from several protocols that use the same band, such as Bluetooth, Wi-Fi, and ZigBee, is possible (Čolaković and Hadžialić 2018). Given its high power consumption and quick connection, Wi-Fi is a viable option for the deployment of sensor networks at fixed locations. Since Bluetooth has a small communication range, exceptional security, and high power consumption, it is perfect for short-term, close-range networking. ZigBee offers the advantages of low consumption, low cost, and self-organization, because each node can serve as a relay station for data transmission between close-by nodes. As a result, it makes for the ideal long-distance, large-range sensor networking and enables simple coverage expansion.

WSN The WSN is a multi-hop self-organizing network system created via wireless communication in order to cooperatively sense, gather, and process various data about the observed item in the network coverage area (Srbinovska et al. 2015; Ferentinos et al. 2017). It is made up of a number of sensor nodes, the majority of which are battery-operated. It can be divided into terrestrial WSN and wireless subterranean sensor networks (WUSN). Lower frequency wireless solutions are preferred for agricultural sensors, which are often buried in the ground, because of WUSN's low attenuation. In comparison to terrestrial WSN, WUSN also consumes more energy and has larger antennas (Ojha et al. 2015). IoT may no longer require a mesh-style WSN with power-based routing, where one node forwards packets of other nodes, as low-power wide-area network (LPWAN) technology develops.

Cloud Computing Cloud computing is the on-demand provision of computer system resources, particularly data storage (in the form of cloud storage) and processing power, without the user's active involvement. Cloud computing is a result of distributed computing, parallel computing, and network computing. A variety of hardware, infrastructure, platform, software, and storage services are offered for IoT applications via this Internet-based computing system. A system for dynamically assigning, deploying, monitoring, and reallocating pools of virtualized computing and storage resources is at the heart of it (Hashem et al. 2015). This system enables users to access compute, data storage, and platform services that adhere to quality-of-service criteria. This will have a significant impact on the expansion of IoT in agriculture. First, cloud computing has made it possible for farmers to store text, pictures, videos, and other types of agricultural data using inexpensive data storage services, which has considerably reduced the cost of storage for agricultural businesses (Nativi et al. 2015). Second, relying on farmers' technical expertise to make decisions using this raw data is challenging. Cloud computing is the only technology that can support intelligent large-scale data processing systems (Ferrández-Pastor et al. 2016). Third, using cloud computing can create a safe environment for developing different IoT applications, such as monitoring agricultural activities (Botta et al. 2016).

Edge Computing Edge computing, as defined by Satyanarayanan (2017), is a new computing model that makes advantage of calculations at the network's edge. Any computer and network resources between the data source and the cloud computing center path are referred to as the edge of edge computing. Cloud services are represented by the edge's downlink data, IoT services are represented by the edge's uplink data, and both are represented by the edge's uplink data. Edge hormone, which shifts some of the computing activities to the network edge device, can improve data transmission performance, guarantee real-time processing, and lower the computational load on the cloud computing center. Because processing occurs close to the source rather than in the cloud, edge computing also provides greater data security (Shi et al. 2019a, b).

Machine Learning A sophisticated method known as machine learning (ML) allows computers to learn new knowledge, continuously improve their performance, and reach perfection. Theoretical, algorithmic, and practical advances in machine learning have been made recently (Biamonte et al. 2017), and it has been combined with other agricultural technologies to optimize crop output while reducing input costs (Shi et al. 2019a, b). The main machine learning methods include naive Bayes, discriminant analysis, K-nearest neighbor, support vector machines (SVM), K-means clustering, fuzzy clustering, gaussian mixture models, artificial neural networks (ANN), deep learning (Ojo and Zahid 2022), decision tree algorithm, and others (Edwards-Murphy et al. 2016). A theoretical framework for agricultural decision-making is provided by ML, which can make accurate predictions, reveal the internal linkages between jumbled, modelless, and complex agricultural data and discover these relationships. Machine learning technologies are useful for intelligent irrigation planning, crop breeding, disease detection, pest and disease prediction, and agricultural expert systems (Russell and Norvig 2018). For instance, historical farming data may be examined using machine learning technology, along with crop productivity under varied climatic conditions and the inheritance of a particular phenotype. Furthermore, by utilizing ML technology, it is feasible to look at association rules and then develop a probability model to identify the genes that are most likely to be involved in the expression of a particular desired trait in the plant (Montesinos-López et al. 2019). This can help the breeding specialist create a breeding experiment that will be effective. The method used three processes to identify the maturity of a single intact tomato using machine learning: pixel-based segmentation, blob-based segmentation, and individual fruit detection. Using criteria including color, shape, texture, and size, decision trees were built in the first two steps and then utilized to segment photos. The different fruit of each tomato was finally automatically identified using the X-means clustering technique. Their method has a precision of 0.88 and a recall of 0.80, per the results of the tomato detection picture test (Kyosuke et al. 2014).

Big Data Protected agriculture generates millions of dynamic, intricate, and geographical data points, including soil databases, greenhouse environment data, animal vaccination records, and government investment data. Contrary to relational data structures, which logically express themselves using two-dimensional tables, agricultural data is more unstructured and contains many hypermedia elements, including expert experience, knowledge, and agricultural models in the form of text, charts, pictures, animations, and voice/video. The four characteristics that best sum

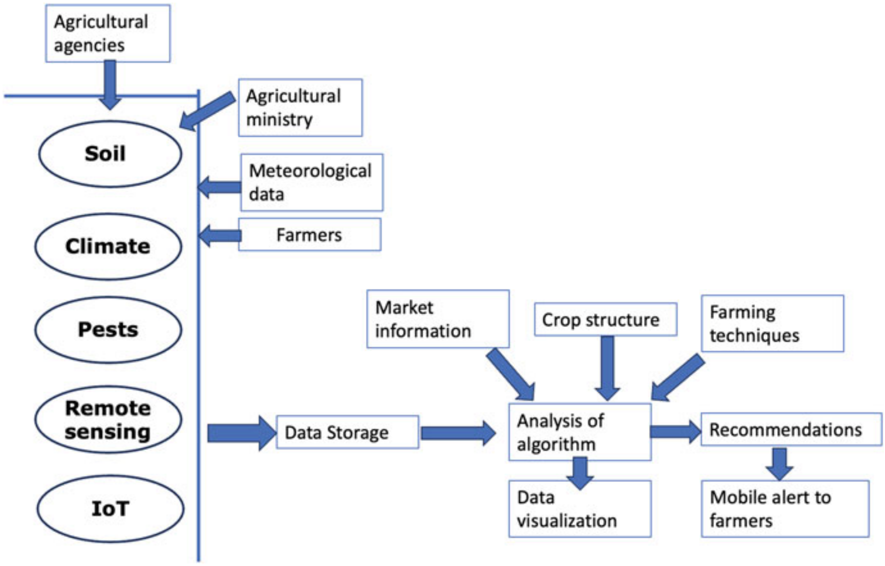

Fig. 8 Big data technology

up how "big" these data are volume, velocity, diversity, and honesty (Zhou et al. 2016). Big data technology can find new knowledge, discover hidden connections within a data collection, and provide data support for subsequent processes. This is done by employing information mining and other techniques. The methods that are most frequently used to deal with big data technology are image processing, modeling and simulation, machine learning, statistical analysis, and geographic information systems (GIS) (Kamilaris et al. 2017) (Fig. 8).

1.5.2 IoT and Plant Management

By using greenhouse technology, which is partially uncontrolled by the natural environment and promotes the intense and efficient use of agricultural resources, protected agriculture, as opposed to open-field farming, offers a more favorable and manageable environment for crop growth. Numerous studies have shown that building and testing various monitoring and control systems to alter greenhouse environmental parameters, like air temperature and humidity, light intensity, and CO_2 concentration, are both technically feasible and economically viable (Sreekantha and Kavya 2017). At the early phases of IoT development, the environmental data are simply processed and frequently provided in sheet and plot form (Mat et al. 2016).

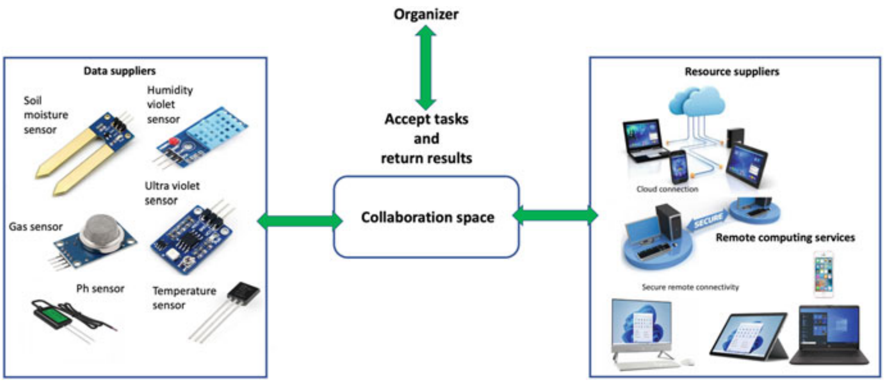

Fig. 9 Conceptual image of IoT-based agricultural solutions

With the development of cloud computing, ML, etc., IoT solutions may easily achieve smart data processing and analysis at low cost and in a straightforward manner (Elijah et al. 2018). Deng et al. (2018) built a closed-loop control system in a factory that makes salad-growing plants based on the kinetic model. Zamora-Izquierdo et al. (2019) developed a low-cost smart agricultural Internet of Things infrastructure based on edge and cloud computing for soilless culture greenhouses. There were three parts to the platform: local, edge, and cloud. While the edge component handled primary management responsibilities and might improve the stability of these systems, the local component dealt with data collecting and automatic control via cyber-physical systems. Data analyses were performed by the cloud component. When compared to a standard open control, the platform conserved more than 30% more water (Liao et al. 2017). According to Zamora-Izquierdo et al. (2019), an online watering system for hydroponic greenhouse crops increased water and fertilizer use efficiency by 100%. Liao et al. installed an IoT-based system in an orchid greenhouse to monitor environmental factors and the growth status of Phalaenopsis. The suggested method might provide high spatiotemporal resolution quantitative data to flower growers and aid in the future improvement of phalaenopsis farming practices (Katsoulas et al. 2017). For a conceptual representation of IoT-based agricultural solutions, see Fig. 9.

Crop growth is greatly threatened by diseases and insect pests, and conventional technology and chemical prevention have several drawbacks and harmful effects (Larsen et al. 2019). Because of the development of IoT, crop disease and pest control now have more intelligent and effective solutions. Numerous IoT sensor types may collect information about location, greenhouse environment state, crop development, and pest situation anywhere in real time, helping farmers to keep an eye on agricultural pests and diseases. Following transmission to cloud data centers, the raw data and photos are processed and evaluated using a range of models and algorithms based on different diseases and pests (Pixia and Xiangdong 2013). The following services are often provided to farms by these cloud computing facilities: disease or pest detection, disaster warning and warning of approaching calamities, and expert system-recommended governance activities. The diagnosis and early warning of agricultural illnesses, as well as online monitoring, should therefore be the main areas of future research.

The source of all IoT data is sensing. The agri-food industry produces a significant amount of heterogeneous datasets with the help of many IoT devices, both in terms of content, structure, and storage type (Lokers et al. 2016). According to Ahmed et al. (2019), big data frequently demonstrates heterogeneity, variety, unstructuredness, noise, and excessive redundancy. Such enormous datasets require sophisticated methods for data curation and storage, as well as time-consuming statistical methods and programing models to extract relevant data. The knowledge required to understand the state of the (agri-food) system is produced through the preprocessing and conditioning of raw data. By employing sophisticated algorithms, observing the system's performance in respect to the desired outcomes, and allowing the system to make independent localized judgments and take the necessary actions, a system can be created capable of doing so. An IoT system is deemed "intelligent" when it reaches this level of independence, which permits autonomy in sensing, decision-making, and actuation (Misra et al. 2022).

1.5.3 AI in Digital Agriculture

The imitation of human intelligence functions by machines, especially computer systems, is artificial intelligence. Vendors have been rushing to highlight how AI is used in their goods and services as AI buzz has grown. Frequently, what they classify as AI is just a part of the technology, like machine learning. For the creation and training of machine learning algorithms, AI requires a foundation of specialized hardware and software. Python, R, Java, C^{++}, and Julia all offer characteristics that are well-liked by AI engineers, yet no one programing language is exclusively associated with AI.

In commercial IT, the phrases artificial intelligence (AI), machine learning (ML), and deep learning (DL) are frequently used interchangeably (van Dijk et al. 2021) (Fig. 10a). However, there are differences. The 1950s saw the invention of the term "AI," which describes devices that mimic human intelligence. As new technologies are created, it encompasses a set of skills that is constantly changing. Machine learning and deep learning are examples of technologies that fall under the category of AI (Madakam et al. 2022). With the aid of machine learning, software programs may predict outcomes more accurately without having to be expressly programed to do so. In order to forecast new output values, machine learning algorithms use historical data as input. The availability of big datasets for training increased the effectiveness of this strategy significantly. Deep learning, a branch of machine

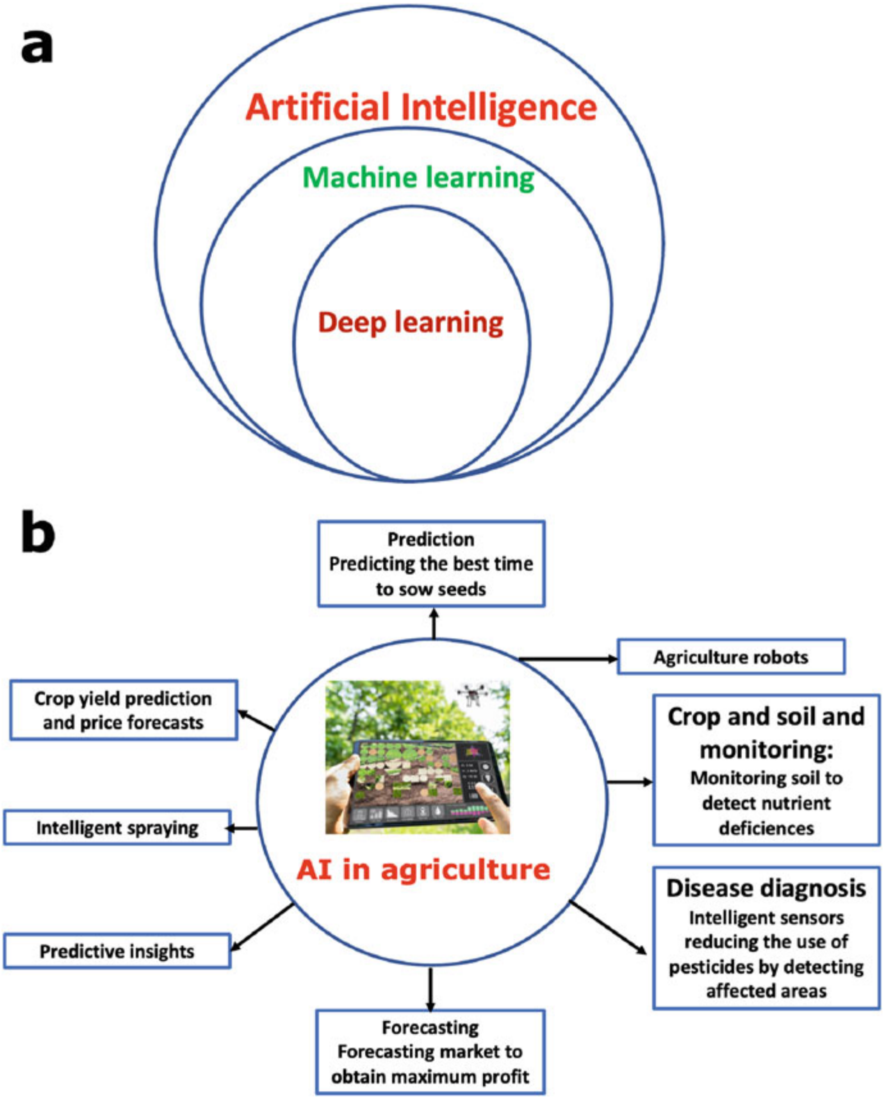

Fig. 10 (**a**) The phrases artificial intelligence (AI), machine learning (ML), and deep learning (DL) are frequently used interchangeably. (**b**) AI-based technologies assisting to increase efficiency across all fields

learning, is based on our knowledge of the anatomy of the human brain. Recent developments in AI, such as self-driving cars and ChatGPT, are underpinned by deep learning's usage of artificial neural networks' structure.

In addition to managing the challenges faced by various industries, including the various fields in the agricultural sector, such as crop yield, irrigation, soil content sensing, crop monitoring, weeding, and crop establishment, AI-based technologies also help to increase efficiency across all fields (Kim et al. 2008) (Fig. 10b). In order to supply high-value AI applications in the aforementioned industry, agricultural robots are constructed (Talaviya et al. 2020). The agricultural industry is experiencing a problem as a result of the rising worldwide population. AI has the ability to provide a crucial remedy. AI-based technical advancements have allowed farmers to increase output while using less input, improve output quality, and ensure a quicker go-to-market for the produced crops. Farmers were using 75 million linked devices in 2020 (Talaviya et al. 2020). The typical farm is anticipated to produce an average of 4.1 million data points per day by 2050.

Over the past few decades, the agriculture production systems have had a great deal of difficulty due to changes in the climate, rising production costs, declining water supplies for irrigation, and an overall decline in farm labor (Jung et al. 2021). In addition, the COVID-19 pandemic poses a threat to the disruption of supply chains and food production. Such elements pose a risk to the environment's sustainability as well as the continuity of the current and future food supply chain. To keep ahead of the ongoing effects of climate change, significant inventions are constantly required (Talaviya et al. 2020). The obvious challenge here is how to produce enough food to feed the world's expanding population. The various ways in which AI has contributed in the agricultural sector are as follows:

Image Perception and Recognition

According to Lee et al. (2017), there has been an increase in interest in autonomous UAVs recently. Some of these applications include recognition and surveillance, human body detection and geolocation, search and rescue, and the detection of forest fires (Tomic et al. 2012). Drones or unmanned aerial vehicles (UAVs) are becoming more and more popular because of their adaptability and amazing imaging technology, which ranges from delivery to photography, the ability to be piloted with a remote controller, and the devices' dexterity in the air, which allows us to do a lot with these devices.

Workforce and Skills

Artificial intelligence enables farmers to compile vast amounts of data from public and government websites, analyze it all, and give farmers answers to many ambiguous problems (Panpatte 2018). It also gives us a smarter way of irrigation, which increases the farmers' yield. A combination of technology and biological talents will be used in farming in the near future as a result of artificial intelligence, which will not only improve quality for all farmers but also reduce their losses and workloads. According to the UN, by 2050, two-thirds of the world's population would be living in cities, necessitating a reduction in the load on farmers (Talaviya et al. 2020). AI in agriculture can be used to automate many operations, reduce risks, and give farmers with relatively simple and effective farming.

Increase the Output
Variety selection and seed quality determine the maximum performance level for all plants (Ferguson et al. 1991). Emerging technologies have aided in crop selection and even improved the selection of hybrid seed options that are most suited to farmer demands. It has been implemented by studying how the seeds react to varied weather conditions and soil kinds. Plant diseases can be reduced by gathering this information. We can now meet market trends, yearly outcomes, and customer needs, allowing farmers to maximize agricultural returns more efficiently.

Farmers' Chatbots
The conversational virtual assistants that automate conversations with users are known as chatbots. With the use of machine learning and artificial intelligence-powered chatbots, we can now understand natural language and communicate with users more personally. Agriculture has made use of this facility by supporting the farmers in receiving answers to their unanswered queries, for offering them counsel, and for providing other recommendations as well. They are mostly equipped for retail, travel, and media.

Machines that are used on farms to hoe and harvest crops, perform weeding, use drones to spray weeds and pesticides, and gadgets used in automatic milking are a few examples of AI-based agricultural technologies (Ryan et al. 2021). Robotics have assisted in an 80% reduction in the amount of herbicides sprayed on crops (Revanth 2019). According to studies, this optimization can reduce pesticide and herbicide costs by 90% while also protecting the environment from the negative consequences of chemical use (Revanth 2019). Drone-captured images of crops can be utilized for a variety of purposes, including nutrient deficiency monitoring, farm animal health monitoring, and agricultural cultivation optimization (Marvin et al. 2021).

On the basis of a given dataset, machine learning (ML) creates algorithms that learn to carry out particular tasks. It is a branch of artificial intelligence that is extensively employed in both academia and business. Between supervised and uncontrolled learning, there are significant differences. A predictive model is improved through supervised learning by setting its parameters to perform well on labeled training data, which consists of inputs and known outcomes. The generated models can then forecast new test data that hasn't yet been seen. On the other hand, unsupervised learning looks for patterns in unlabeled data. It is more difficult to quantify the performance of an unsupervised model compared to supervised methods (van Dijk et al. 2021).

1.5.4 DL, Genomics and Breeding

As was previously stated, there are two basic categories of ML problems: supervised and unsupervised. The goal of supervised learning is to create a model that associates predictors with target variables, such as histone marks, such as DNA sequences. Target variables might be either continuous (regression) or categorical (classification). The prediction of regulatory and nonregulatory regions in the maize genome (Mejia-Guerra and Buckler 2019), the prediction of mRNA expression levels (Washburn et al. 2019), sequence tagging in rice (Do et al. 2018), plant stress phenotyping (Ghosal et al. 2018), and the prediction of macronutrient deficiencies in tomatoes (Tran et al. 2019) are a few examples of supervised learning applications. The issue becomes unsupervised if there is no information about the outcome in the data collection (Wang et al. 2020).

In order to solve complicated biological challenges, deep learning has been utilized in the fields of genomics, transcriptomics, proteomics, metabolomics, and systems biology (Xu and Jackson 2019). Numerous studies demonstrated that DNA shape significantly influences the specificity of transcription factor (TF) DNA-binding (Lai et al. 2019). Chromatin accessibility assays (like MNase-seq, DNase-seq, and FAIRE) and other genomic assays (such microarray and RNA-seq expression) are only a few of the many data types that are available. The same is true for transcription factor (TF) binding, which can be studied using ChIP-seq data, gene expression profiles, DNA affinity purification sequencing (DAP-seq), and ampDAP-seq, which uses amplified and consequently demethylated DNA as substrates and histone modifications (Zampieri et al. 2019).

Several deep learning techniques were created to model TF DNA-binding specificity and analyze these enormous datasets (Wang et al. 2020). Several deep learning-based techniques have been developed to predict in vivo TF binding. For instance, DeepBind can learn several motifs to forecast the binding sites of proteins that bind DNA and RNA (Alipanahi et al. 2015). Cell-specific TF binding is predicted by TFImpute (Qin and Feng 2017). In DeepSEA (Zhou and Troyanskaya 2015), DeFine (Wang et al. 2018), and DFIM (Greenside et al. 2018), the impacts of functional noncoding variations were assessed. DRNApred was created (Yan and Kurgan 2017) to distinguish between residues that bind to DNA and those that bind to RNA.

It is difficult to pinpoint the important genomic regulatory regions in species like maize, which have a large number of repeated elements and broad intergenic areas. In order to overcome these difficulties, techniques like k-mer grammars, which are based on natural language processing, have been employed to precisely and cheaply annotate regulatory areas in maize lines. Modeling transcription factor binding locations has benefited significantly from machine learning techniques. Several facets of plant biology have shown the effectiveness of machine learning models. For better in vivo transcription binding sites (TFBSs) prediction, they can be trained using several types of sequencing data, either separately or in combination, and they can also further integrate additional data, such as DNase I hypersensitivity data.

1.6 Remote Sensing Technologies

The agricultural community now has a diagnostic tool thanks to remote sensing (RS) technology that may serve as an early warning system. This enables quick action to stop any problems before they spread widely and negatively impact crop productivity. The agricultural community now has access to a variety of RS options as a result of recent advancements in sensor technologies, data management, and data analytics. However, the agriculture business has not yet fully utilized RS technologies due to knowledge gaps about their sufficiency, suitability, and techno-economic viability. The use of RS technologies in agricultural production has increased significantly over the past 20 years, while use of unmanned aerial systems (UASs) has increased significantly since 2015. The region that produced the most research articles concerning UASs was Europe (34% of the total), followed by the USA (20%) and China (11%) (Khanal et al. 2020). Prior RS research tended to concentrate more on soil moisture and crop health monitoring during the growing season and less on issues like soil compaction, subsurface drainage, and crop grain quality monitoring.

Modern technology have always been used by agricultural research experts as they look for new methods to incorporate them into agricultural systems. Dynamic crop simulation models have proven helpful tools for integrating various agriculture system components and enabling us to investigate how those components operate within the system. Because of its ability to utilize huge data, which is now more readily available through the use of unmanned aircraft systems (UASs), it is currently attracting a lot of attention within the agriculture disciplines (Jung et al. 2021). By enabling advanced analytics for managing agricultural systems, UAS offers a previously unheard-of-chance to increase production systems' resilience and efficiency (Lezoche et al. 2020).

1.7 Precision Agriculture Technologies for Crop Production

Precision agriculture (PA) enables the agro-management by using advanced technology sensor and analysis tools. PA employs a huge volume of data and information to progress the use of agricultural resources, yields, and the quality of crops (Singh et al. 2020) and drought-related decisions in agriculture (Rhee and Im 2017). The changing weather and its effect on ecosystem threaten crop production and food security for the present and future generations. Machine learning approaches have been applied for the management of agri-related factors such as water availability, soil fertility, environment and diseases/pests (Priya and Ramesh 2019). Smart, digital agriculture can also benefit from the integration of the IoT devices, smart systems, and sensors to enable farmer's agri-practices (Chehri et al. 2020). Among the PA applications, remote sensors, GPS, GIS, and yield maps are among the most in use (Cisternas et al. 2020). Other tools that have shown great interest for PA include UAVs and WSNs for diverse functions including aerial crop monitoring and smart spraying tasks (Radoglou-Grammatikis et al. 2020).

PA ensembles a huge amount of information about the crop status or crop health in the growing season at high spatial resolution. Independently of the data source, the most crucial objective of PA is to provide support to farmers in managing their farming practices. Several agro-related variables, such as soil condition, plant health, fertilizer and pesticide effect, irrigation, and crop yield, have to be efficiently managed to realize higher yield and better crop growth under natural and environmentally challenging conditions (Abdullahi and Sheriff 2017). Monitoring all the above with precision is important for rational use of farming resources and their management (Wu et al. 2022). Remote sensing methods like satellite- and UAV-based hyperspectral imaging offer solutions as biophysical indicator maps during the various stages of crop growth cycle and seasons (Bégué et al. 2018; Wu et al. 2022) besides soil and plant health. Other tools like AI and ML have also been useful in precision agriculture for prediction and appraisal of crop yield, detection of diseases, and weeds (Liakos et al. 2018) (Figs. 11 and 12).

1.8 Conclusion and Recommendations

The use of big data in food production, along with the implementation of the Internet of Things (IoT), blockchain technology, artificial intelligence (AI), machine learning, cloud computing, as well as unmanned aerial vehicles (UAVs), and

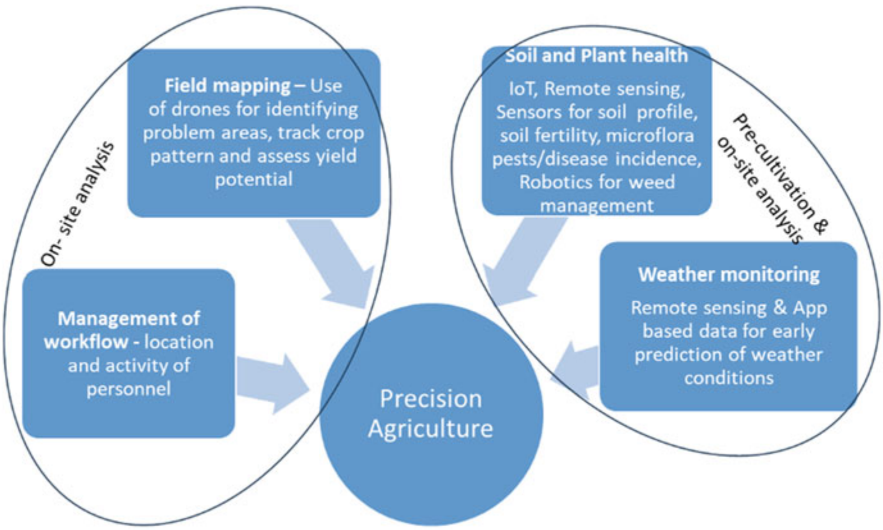

Fig. 11 Diverse applications of precision agriculture

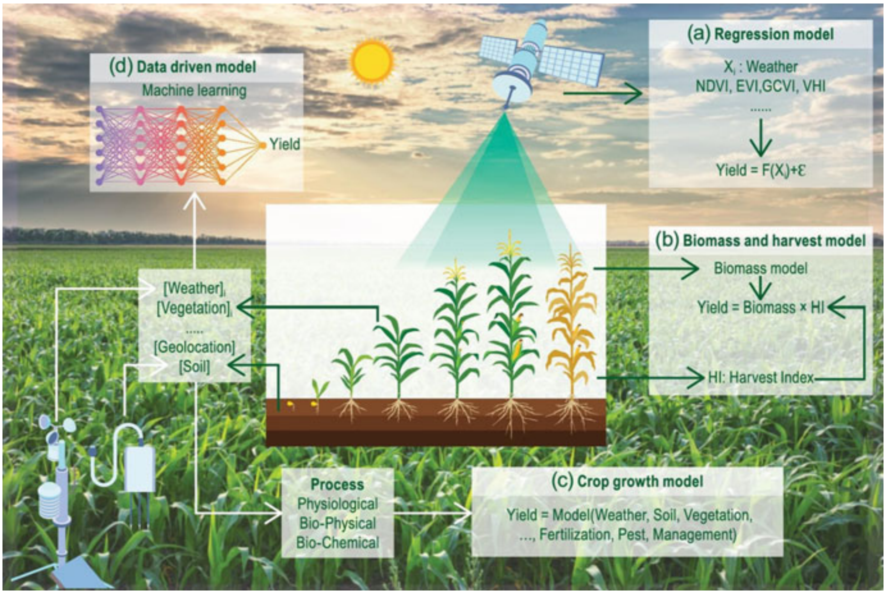

Fig. 12 Crop yield prediction methods. (**a**) regression method; (**b**) biomass and harvest index; (**c**) crop growth model; (**d**) data-driven models. (Courtesy: Wu et al. 2022; doi: https://doi.org/10.1093/nsr/nwac290)

robotics, is referred to as framework of digital agriculture. The components of the digital agriculture framework are as follows:

- Basic information databases pertaining to agriculture: These databases include essential information about farmland, genetic resources, weather patterns, social and economic contexts, etc. that is pertinent to agricultural activities.
- A method for acquiring data that can be used to update databases and keep track of agricultural activities in real time (or almost real time). This system is made up of digital data collectors that are tasked with collecting information from aerial or satellite-based sensors, above- and below-ground sensors, and data on the weather, plants, and soil.
- Digital network transmission system: This system is a sort of media that enables the distribution of commands and the gathering of data.
- System for central processing in order to control the functioning of digital agricultural machinery, cyber physical system (CPS) assesses all the information amassed and develops feasible judgments using GIS, agricultural models, and expert systems.
- Digitized agricultural machinery (DAM): This category comprises tools for harvesting, seeding, and managing fertilizer and water. As digital agricultural machinery performs CPS commands and returns processing results either directly

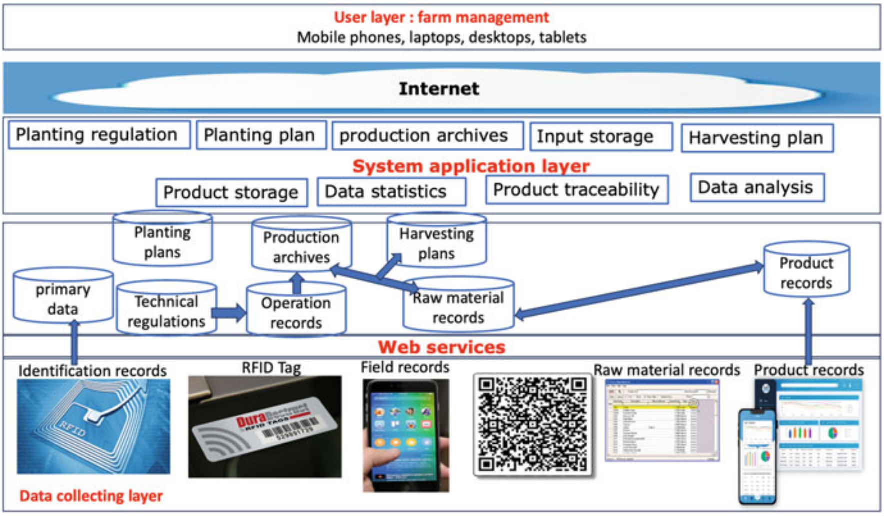

Fig. 13 Framework of digital agriculture (Radio frequency identification (RFID) refers to a wireless system comprised of two components: tags and readers. The reader is a device that has one or more antennas that emit radio waves and receive signals back from the RFID tag)

or through a real-time (quasi real-time) information collecting system, it uses digital networks, GPS, and GIS to assist it (see Rijswijk et al. 2021 for details).

The framework for digital agriculture is shown in Fig. 13. Each component is connected by a common data interface. A computerized agricultural system that uses core information databases to set the planting schedule for a year also monitors crop growth vigor and provides data on soil structure, water content, disease, weather, and other important elements. Digital agriculture technology is used to carry out a series of operations, such as planting, controlling water or fertilizer, harvesting, and sending the data back to CPS. CPS does thorough information analysis before making decisions. The whole analysis' report is then produced by CPS. The interconnected development of each component is underlined in digital agriculture. The foundation for digital agriculture can only be laid when all the parts are perfectly connected and advance at the same time. The phrase "digital agriculture" cannot be used to describe a single element or a group of elements that are developing separately.

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