# Smart Agriculture: A Comprehensive Overview

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# Smart Agriculture: A Comprehensive Overview

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**Abstract** The world population is anticipated to increase by 2 billion by 2050 causing a rapid escalation of food demand. A recent projection shows that the world is lagging behind in accomplishing the "Zero Hunger" goal, in spite of some advancements. Socio-economic and well-being fallout will affect food security. Vulnerable groups of people will suffer malnutrition. The agricultural industry must be upgraded, smartened, and automated to serve the growing population. Adopting existing technologies can make traditional agriculture efficient, sustainable, and eco-friendly. In this survey, we present *Agriculture 4.0* and its applications, technology trends, available datasets, networking, and implementation challenges. We concentrate on Artificial Intelligence (AI) and Machine Learning (ML) technologies that support automation, as well as the Distributed Ledger Technology (DLT) which provides data integrity and security. Following an in-depth investigation of several architectures, we also provide a framework for smart agriculture that relies on the location of data processing. Open research problems of smart agriculture have been discussed from two perspectives - technology and communications. AI, ML, DLT, and Physical Unclonable Function (PUF) based hardware security fall under the technology group, whereas any Internet-based attacks, fake data injection and similar threats fall under the network research problem group. The survey aims to provide an in-depth study on recent works, challenges, and open research problems of smart agriculture to the researchers in this domain.

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## 1 Introduction

By the end of the 21$^{st}$ century, world population is expected to reach 11 billion [9] and food consumption will surge at an unprecedented rate. Though a "Zero Hunger" goal by 2030 has been set, we are lagging behind the target [10]. It is estimated that about 800 million people are starving across the globe as of now [64]. Population increase makes the situation worse. To feed the world, food production is required to increase to 170% by 2050 [11].

A number of other factors are aggravating this situation: Firstly, urbanization is changing our diet. People now eat more animal protein than before. Annual consumption of animal protein per person from 1997 to

1999 was 36.4 kg and is expected to increase 20% by 2030. Secondly, natural resources are exhausted. Agricultural lands are becoming unsuitable for farming. Twenty-five percent of the current arable land is not at all suitable and 44% is reasonably not suitable as of now. Due to water scarcity, 40% of the arable land is turning to unproductive land. Thirdly, urban expansion and deforestation for new arable lands also lead to rapid depletion of groundwater. Over-cultivation has also led to shorter fallow periods and reduced crop rotation whereas overgrazing leads to soil erosion. Food waste is another issue. 33% - 50% of the food is wasted worldwide. Finally, climate change is progressing very fast. It started affecting every aspect of food production. Over the last 50 years, greenhouse gas emissions have doubled with unpredictable rainfall and more instances of droughts and floods.

To combat these problems, the food and agro industries embrace "Agriculture 4.0", a smart and green movement, centered on science and technology [148]. Traditional farming is changing to viable, intelligent, efficient and environmentally friendly farming. New terms such as "smart farming," "digital farming," and "precision farming" are emerging. "Smart farming" is the same as "Smart Agriculture". Smart farming focuses on accessing data and using it to optimize complex systems and improve crop quality and yields. It also reduces human labor whereas precision farming targets optimization, precision, and crop specific solutions. The combination of the two is "digital farming." Fig. 1 shows the advantages of smart agriculture over traditional agriculture.

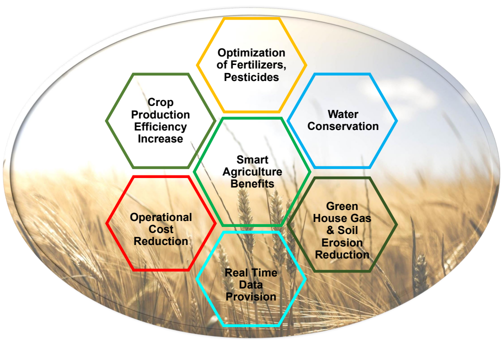



**Fig. 1** Smart Agriculture Benefits Over Traditional Agriculture.

The majority of the survey works on smart agriculture address a specific area of research, e.g. either cybersecurity or AI. However, an overall idea of the research domain that provides a complete picture of smart agriculture is necessary for driving research in this important area of high social impact. In this survey we discuss "Agriculture 4.0" a.k.a. "smart agriculture" and its applications, trends, technologies, networking, datasets, challenges, and open research problems. This survey will provide a holistic information perspective on smart agriculture to researchers.

The rest of this survey is organized into eight sections. Internet-of-Agro-Things (IoAT) based Agriculture Cyber Physical Systems (A-CPS) are discussed in Section 2. Section 3 presents the smart agriculture architecture. Various applications of smart agriculture are described in Section 4. Challenges in implementing smart agriculture are presented in Section 5. Section 6 describes different technologies adapted in smart agriculture, whereas Section 7 discusses available datasets in the agricultural industry. Section 8 talks about the open research problems for the future and finally Section 9 concludes the paper.

## 2 IoAT based A-CPS

The Internet of Things (IoT) refers to physical things and devices with unique id connecting and sharing data through the Internet. Incorporating IoT in physical systems creates cyber physical systems (CPS). CPS is a mixed system of hardware and software. Defining any problem through CPS makes the process robust, seamless, and risk free and solves the problem optimally. The idea of CPS can be applied to any industry. When it comes to the agricultural industry, problems are defined through agricultural cyber physical systems (A-CPS) [149,151]. Any IoT based smart agricultural system comprises of the stages described in Table 1. Locations of the occurrence of various stages have changed before and after the *tinyML* era [241].

## 3 Smart Agriculture Architecture

After careful consideration of various architectures [66, 67,78,112,118,156,186,235] in the literature, we present the architecture of smart agriculture with three main layers and two connecting layers. Fig. 2(a) shows this architecture. Here, layers are defined according to the location (proximity to the occurrence) and their connections.

### 3.1 Layer-1

*Agriculture Device Layer* is the first layer or the bottom most layer. It consists of sensors, animal paddocks, greenhouse, UAV, agro robots, automated tractors [5,

**Table 1** A-CPS Workflow Information.

| Stages | Descriptions | Before TinyML Era | TinyML Era |
|---|---|---|---|
| Data Collection | Things collect data. | Sensor level. | Sensor level. |
| Data Processing | Makes the collected data usable to the model. | Edge level | Edge level |
| Prognostic | Analyze the processed data using preset rules. | Cloud/Edge level. | Edge level |
| Solution | Solution of the issue is suggested. | Cloud/Edge level. | Edge level |
| Measures Taken | As per the solution, measures are taken. | IoT device level. | IoT device level. |

6]. Data is collected and sensed in this layer. The devices, also known as distributed source nodes, monitor physical parameters and collect data in real time and transmit it to the gateway node at the next tier via the connectivity layer, thereby creating a Wireless Sensor Network (WSN). Fig. 2(b) depicts the information gathered by numerous sensors and cameras in various smart agriculture applications. For example, underground sensors and cameras on UAVs can gather data in a rice field and deliver it to the edge for analysis.

### 3.2 Layer-1a

This layer is in between layer-1 and layer-2. It is called *Connectivity Layer-1*. Layer-1 sends data to layer-2 through this layer. Different networks are used for different coverage areas as in Fig. 2(c). Depending on the application, various long and short range networks are chosen. For example, near range ZigBee, Wi-Fi, Z-Wave, Bluetooth, RFID, and NFC are used to send data from agriculture devices to the edge computing layer, while SigFox, LoRaWan, and NB-IoT are utilized for longer ranges [71]. Z-Wave is a good solution for a small farm in a distant community with restricted network connectivity. LoRaWan's low energy use and long distance transmission suit larger farms. Bluetooth low power is utilized for monitoring soil, air, and water management systems [84] and ZigBee for irrigation [131]. RFID technology is employed in smart agriculture for various purposes [80,116,175,189,208,233]. The work in [255] used LoRa for water management purposes.

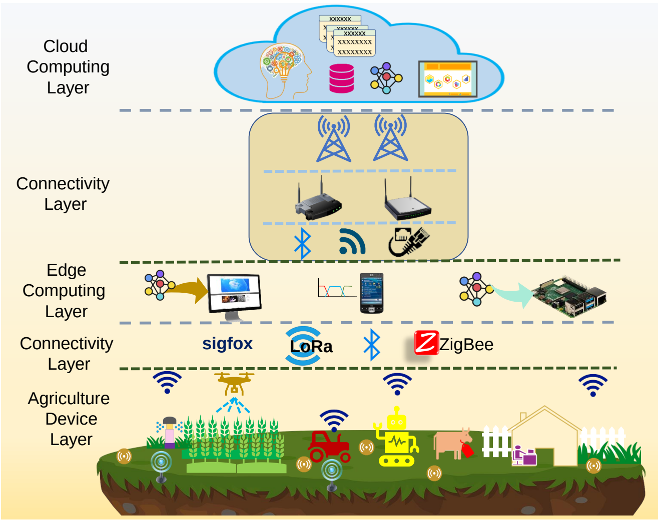
### 3.3 Layer-2

*Edge Computing Layer* is the second layer from the bottom. It consists of edge nodes. Data processing and encryption are performed in this layer. Because of the resource constraints at the edge layer, the prognostic and solution components were previously handled in the next layer. However, trained ML models can now compute and predict at this layer because of current hardware and AI edge developments. Both prognosis and inference can be done in the next layer if the work is resource intensive or not time sensitive. The edge computing layer, for example, performs the appropriate measures and notifies the farmer if a cow leaves its supposed territory in a livestock farm or needs milking.

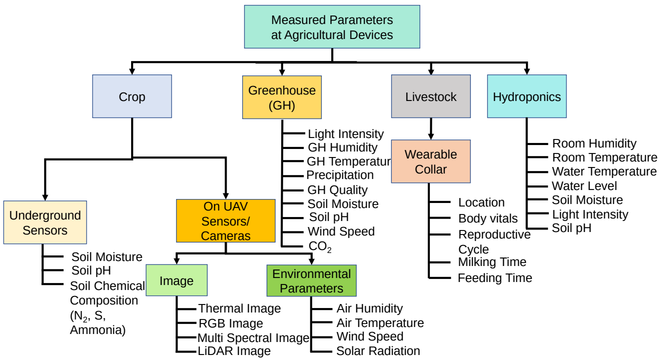
For edge-AI initiatives, prognosis and solutions are also performed here. Various hardware boards are used for processing the data [71] at this layer e.g., Arduino UNO in [201] for a greenhouse application, Raspberry Pi in [136] for hydroponic systems, ESP8266 in [113] for connecting smart agricultural components, ESP32 in [37] for smart irrigation, Intel Edison in [34] for vertical agro warehouses, and BeagleBone in [18] for agrochemical process monitoring.

### 3.4 Layer-2a

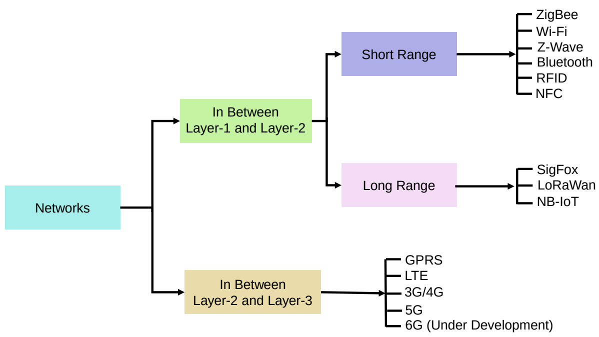
This the second connectivity layer. It is called *Connectivity Layer-2*. The edge computing layer sends data to layer-3 through this layer. Different networks are used for data transmission depending on the application needs. Fig. 2(c) lists the networks used in this layer. Cellular technologies including GPRS, LTE, 3G/4G, and 5G are used to send processed data from edge computing to the cloud. 5G features low latency, high dependability, wide coverage, fast data rate, and new frequency bands [235]. These features may boost communications capability of the smart agriculture. In [128], GPRS has been used for irrigation. New 5G initiatives have been presented in [15,65]. 6G cellular technology is the 5G network's successor. It's faster than current mobile networks. Smart agriculture will benefit from flexible decentralized models in edge computing, AI, and blockchain. Cloud management, framework, and integration with applications have been discussed for smart agriculture in [202]. A general smart cloud based system has been presented to facilitate smart farm remote sensing [104]. UAVs are being used as flying edge computing platforms to provide connectivity as and when needed [224]. Federated learning based approaches are




(a) Multi Layer Architecture of Smart Agriculture.




(b) Sensor Parameters measured in Agriculture Device Layer of Smart Agriculture Architecture.




(c) Networks used in Connectivity Layer of Smart Agriculture Architecture.

**Fig. 2** Smart Agriculture Architecture Details.

also being used to address security and data privacy violation issue [119].

### 3.5 Layer-3

This is the topmost layer. It is called *Cloud Computing Layer*. It stores data for future use. This layer is accessible through the Internet [78]. It was the computing and decision taking layer until recently [112, 128, 156], specially before tinyML. The cloud's high computational capacity enables it to complete a variety of complex jobs in an acceptable amount of time. However, cloud computing's limitations necessitate the emergence of new computing paradigms. Latency, high Internet bandwidth needs, data security and privacy are some of the limiting problems that impede the time-sensitive monitoring and management of intelligent agriculture.

## 4 Smart Agriculture Applications

In this section, application areas of smart agriculture are discussed. Fig. 3 shows some application areas of smart agriculture.

### 4.1 Crop Management

Analysis of economic, ecological, and social factors that go into crop selection, growing, and marketing is referred to as "crop management."

Cropping patterns are influenced by elements such as crop growth, water availability, labor, insurance, and environmental conditions. Changes in cropping patterns are influenced by environmental conditions. Traditional crop like rice, which requires a lot of water, cannot be grown in locations where water supplies are drying up and groundwater tables are decreasing. Different countries' export and import rules, as well as the agricultural product's market, all have an impact on crop selection. Once a crop has been chosen, the following step is to cultivate the crop. The IoT provides farmers with the most up-to-date technologies and sensors in the field to monitor plant growth. As an example, pests and insects that harm plant growth can be detected using ultrasonic sensors placed in the field. High-frequency sound waves are generated to eradicate pests after they have been detected, and the farmer is advised of their presence for additional assistance [238].

### 4.2 Soil Monitoring

Farming relies heavily on the availability of soil moisture. When a plant is growing it uses photosynthesis, respiration, transpiration, and mineral transport as a means of transporting nutrients. Farm decision-making relies heavily on soil monitoring. There are many elements that influence cropping patterns, including water availability and soil salinity.

**Fig. 3** Applications of Smart Agriculture - Crop Management, Pest Control, Smart Irrigation, Livestock Monitoring Smart Greenhouse, UAV [1].

Soil health can be evaluated with the assistance of these variables. Field sensors collect soil temperature and humidity data, which is then uploaded to the cloud for further analysis. Based on the salinity content, soil nutrient level and soil humidity and temperature, cropping patterns are studied and determined. Water is required for photosynthesis, temperature regulation, and transport of food and nutrients for plant growth, hence soil moisture is an important consideration in the growth process.

For optimal plant growth, humidity governs the delivery of nutrients and the rate of transpiration. The optimal humidity for growing vegetables is between 50% and 60% [251]. A soil moisture sensor embedded in a plant's root analyzes soil moisture levels to ensure that water resources are optimally utilized [130, 182]. Soil conductivity has been measured along with soil moisture at low cost using RF propagation in available Wi-Fi bands [57]

### 4.3 Smart Irrigation

The use of cutting-edge irrigation technologies to improve crop quality and quantity is known as "smart irrigation." It saves water by watering plants in the most efficient way possible. There are two types of irrigation systems: (1) weather-based and (2) soil moisture sensor-based. An irrigation controller receives data from a local weather station and adjusts the amount of water. Sensors embedded in trees/grass correctly measure soil moisture. This sort of irrigation necessitates the use of precise humidity and air temperature measurements, as well as weather monitoring and knowledge of the field's cropping pattern. Sprinklers, for example, are actuated when data is transferred to the cloud [191].

The irrigation schedule for each farm area is determined by the sensor readings from the soil moisture probes. Optimal crop growth and 100% water efficiency can be achieved by precise irrigation scheduling and efficient actuation [158]. The irrigation system may be controlled by farmers using a smartphone app. Temperature, humidity, soil moisture and ultrasonic sensors in the field all feed into this irrigation system [163]. Farmers may activate the irrigation pumps to water their farms using a user-friendly mobile app on their smartphones, which connects to the cloud for analysis and control.

### 4.4 Livestock Monitoring

An important component of smart agriculture is livestock management. Farmers can monitor herd health, track grazing animals, and optimize breeding methods with an IoT-enabled livestock health monitoring system. Wearable collars or RFID tags can be used to measure vital signs like heart rate, blood pressure, and respiration rate in cattle. This serves two purposes: it saves labor while also treating animals in a timely manner, preventing the sickness from spreading further. GPS tracking is used for this purpose in [191]. It also serves to prevent any type of accident from occurring. Using RFID tags for animal identification and tracking is also common practice [240].

### 4.5 Remote Sensing

Farmers can use remote sensing to acquire real-time agricultural data utilizing drones to map farm lands. Using crop health and agricultural information, they can also check crop yield. Remote sensing can map soil conditions and help farmers choose the best soil for a crop. Weeds and pests can be identified and controlled. Remote sensing's most essential use is weather forecasting. It can track rainfall, drought conditions, and water resources, notifying farmers on water availability and weather capital and crop planning can be done in advance [207]. When it comes to predicting production and plant growth, one of the most crucial metrics in crop cultivation, the *Normalized Difference Vegetation Index (NVDI)*, has been used in [220]. Abiotic stress factors are monitored with the finest spatial resolution possible using remote sensing sensors on the farm field [95].

### 4.6 Smart Greenhouse

In the wake of global climate change and dwindling natural resources, the agricultural business welcomes farming approaches assisted by technology. The smart greenhouse is among them. It is an indoor environment specifically designed for the plants. It is a self-contained environment for agricultural monitoring that integrates IoT and AI/ML technologies. It safeguards the farm against wind, storm, and flooding. It boosts production without requiring manual involvement. Inside the greenhouse, solar-powered IoT-sensors are installed to monitor the health of the vegetables, fruits, and other horticultural crops. Using soil moisture sensors installed within the tree's root system, automatic drip irrigation can be carried out. If a predetermined threshold is met, the in-field actuators will water the farm accordingly. LED lighting can better serve the demands of plants. A regulated illumination of a certain wavelength and intensity can improve plant development and yield throughout the year.

Utilizing drip fertigation techniques, suitable amounts of minerals such as potassium, phosphorus, and others are applied to plants for optimal growth and health. As more technologies become available to farmers and the demand for organic fruits and vegetables grown with smart green techniques increases, greenhouse horticulture is becoming smarter [117]. In [223], a decision support-based IoT-friendly smart greenhouse system for enhancing rose plant productivity has been demonstrated.

### 4.7 Unmanned Aerial Vehicles

Unmanned Aerial Vehicles (UAVs), a.k.a. drones, are becoming increasingly prevalent in the contemporary agricultural economy. They are used for mapping crops, monitoring fields, remote sensing, fertigation, and weed detection. Drones can be a lifesaver when photographing vast agricultural tracts, mountainous regions, or remote locales.

To assess crop health, the *Normalized Difference Vegetation Index* (NVDI) is computed using photos captured by a drone. It determines the plant's water level, stress level, nutrient status, and pest infestation. It may steer the entire cultivation process of crops [72,155,183].

### 4.8 Autonomous Tractor

Innovative technologies are transforming the agricultural sector. Industrial IoT (IIoT) has advanced from crop management, soil monitoring, and smart irrigation to pest control, livestock management, and agri-marketing. In the near future, we can anticipate autonomous, intelligent, and smart farming equipment. An autonomous tractor is an integral component of these tools. This is a programmable autonomous vehicle. It can perform cultivation and fertilizer application. They are outfitted with GPS, lasers, and cameras and can operate autonomously without the need for farmer supervision.

Together with these smart tractors, an autonomous drone is employed for weed detection, pesticide spraying, field monitoring, and surveillance for sustainable agriculture [76]. The autonomous tractors used in orchards for spraying and mowing are equipped with a remote-assisted guide for conducting agricultural operations and perception systems for detecting impediments. The perception system employs cameras for obstacle detection and path identification based on geometry [153, 237].

### 4.9 Urban / Vertical Farming

In densely populated cities, the growing urbanization rate poses a serious problem. In these regions, a new way to farming has arisen to provide a sustainable farming option. Consequently, urban or vertical agriculture has gained popularity among urban residents. It occupies three-dimensional (3D) area for agriculture using controlled water, nutrients, minimum herbicides, and artificial lighting. The practical restriction of vertical farming systems is the generation of artificial light sources for plant development, as well as the associated high costs [83].

Hydroponics, as the name suggests, is a water-based system in which plants obtain all of their nutrition from a solution rich in elements. Continuous nutrient input is required in hydroponic systems. Using an app, a microcontroller can water the plants in a hydroponic system, as in in [234]. Aeroponics is similar to hydroponics but roots are misted instead of erupting in water. Aeroponic plants have been found to have a higher concentration of nutrients than hydroponic plants, according to research. This method is used to cultivate plants on board the International Space Station. Aquaponics, a relatively new agricultural method, is a hybrid of hydroponics and aquaculture in which the nutrients (e.g. phosphorus and nitrogen) are not added externally. Those nutrients are produced by the fish in the same tank.

### 4.10 Agriculture Marketing

An essential component of the expansion of a society's economy is the effective distribution of its goods and services. Inflation is caused by the presence of middle men, and as a result, both consumers and farmers suffer losses. Smart agriculture alters this dynamic. Using a variety of agro-marketing apps, farmers are now able to engage in direct consumer sales of their products.

A blockchain based on Ethereum has been utilized as a platform for the purpose of conducting trade talks between farmers and end consumers [187]. With the assistance of blockchain, a food supply chain has been established [41], beginning with the updating of a distributed ledger during the production phase and continuing all the way through to the distribution phase.

### 4.11 IoT Infrastructure

This area covers the IoT infrastructures e.g., various IoT sensors, cameras, connecting networks, efficient data collection, connectivity, low power and low cost devices. Efficient infrastructure increases the yield of a farm. An agricultural IoT platform has been presented in [232] for uninterrupted data collection though various agricultural things like sensors, cameras and UAVs. An asynchronous and reliable Sensor Network over White Spaces is presented in [193]. This bidirectional communication method sends different data to different sensor nodes at the same time and asynchronously receives the data from the nodes sent concurrently. In [188] a life cycle framework for energy efficient IoT in agriculture and its effects on various operational factors have been discussed.

## 5 Smart Agriculture Implementation Challenges

The processes of Smart Agriculture have modernized and facilitated traditional farming methods. However, developing a system for smart agriculture might not be as simple as putting few sensors out in the field to monitor conditions. Precision agriculture comes with a number of advantages, but it also poses a number of challenges for farmers and owners of agricultural businesses. These challenges need to be conquered if increased productivity and profits are to be realized as a result of precision agriculture. In this section, challenges of smart agriculture in modernizing the processes are discussed.

### 5.1 Power Issues

The majority of "smart" agricultural activities involves the use of many machines, the operation of which requires significant quantities of power. It is not uncommon for farms to have quite high power requirements given their typically large land areas and the large number of required electronic components. This has been a significant barrier to the widespread adoption of automated procedures of this kind on large farms. Some of the proposed solutions include the use of clean energy derived from renewable sources such as solar, wind, and hydro, which would supply the machinery with continuous power that would not be interrupted [125]. Numerous researchers have shown an interest in this topic, and work is currently being done to adopt and improve the effectiveness of various renewable energy sources for smart farming [90, 184]. Inconsistent energy needs at various locations across the farm are just one of the challenges presented by these alternative power sources. Other energy or power related challenges include storing and transmitting the power that is generated. To solve these problems, an effective microgrid design must be developed. Research has been conducted in this field to develop an effective smart microgrid which can operate in conjunction with renewable energy sources [56, 61].

### 5.2 Power Consumption

IoT devices are connected through the Internet and generate huge amounts of data. This data is stored at the data centers which consume enormous amount of energy. Manufacturing of IoT devices like sensors, ICs, micro-controllers, and other semiconductor embedded devices also requires a lot of power. Additionally, some IoT devices are battery operated, hence they are required to consume low power. IoT devices are low power devices but transmission of data from machine to machine is one of the major sources of power consumption.

### 5.3 Hardware Availability

A large number of sensors need to be interconnected for a successful IoT process. Once data is collected through "things" in the IoT network, they need to be processed and computed. Hence, hardware availability is another major challenge.

### 5.4 Hardware Security

The number of IoT devices is anticipated to be 50 billion by 2050 [55]. However, security of the hardware is compromised when low price is demanded. For IoT devices, two major security issues are Trojan and Side Channel Attacks (SCA). Hostile hardware modifications by the attacker are performed to manage the device secretly in the case of Trojan attacks. In [50], electron microscope scanning is performed on chips for detecting any additional gates present after comparing with a reference picture. A power efficient device specific Physically Unclonable Function (PUF) is proposed for IoT friendly embedded devices [195]. In the case of SCA, side channel signals e.g., electromagnetic emanation, power profiling and timing analysis, are utilized to obtain secret information like cryptographic keys. In [219], a real life SCA has been presented. Various solutions on hardware-assisted security (HAS) have been proposed in [33, 43, 103].

### 5.5 Physical Security of IoT Devices

Physical security of the hardware is another important challenge. IoT devices are prone to various physical attacks as they are installed outside, sometimes without any surveillance. Signal jamming, replication attack, eavesdropping, and physical damage of the device are some of these attacks [249]. Recently, due to the advancement in edge computing devices, edge initiatives in smart agriculture are gaining attention. Various physical security and safety issues of the IoT devices are addressed and safety measures are proposed in [12, 27, 74, 164].

### 5.6 Networking and Communication

Machine-to-Machine (M2M) communication plays a significant role in IoT based smart agriculture. They work collectively towards a final task. Data is shared through varied networks and communication protocols e.g., ZigBee, Wi-Fi, LoRA, SigFox, LTE, GPRS, and 5G. For a large agricultural farm, it is not a viable option for setting up and maintaining such networks due to the large cost. Various alternative but efficient methods are being proposed in different papers [49, 192, 254]. Other initiatives like SIL-IOT [246] have also been proposed. It is an agriculture thing, made by integrating Solar Insecticidal Lamps (SIL) with WSN for seamless communication. In [98], a LoRa based image transmission system has been proposed which can send the images from field camera.

### 5.7 Connectivity Issue

Unavailability of high bandwidth Internet connection in villages hampers the cloud-centric computation and halts the progress of smart agriculture. Mountains and vast forests obstruct the line-of-sight (LOS) GPS communication [8].

### 5.8 Data Security and Privacy

To maintain data security and privacy, data encryption is a good practice. But due to the simple design of IoAT devices, data encryption is not always a viable option as encryption is a resource intensive process. As a result, smart automated agricultural solutions are vulnerable to various attacks. Yield and quality of the production can be affected negatively.

### 5.9 Scalability and Reliability

The size of agricultural farms varies from small to large. Depending on the size of the farm, the number and types of sensors also vary. As a result, a vast heterogeneous data set is generated from each farm. Hence, scalability plays an important role in smart agricultural solution. Reliability is another important factor. High reliability can reduce the number of redundant devices hence decreases the cost involved.

### 5.10 Big Data Challenge

In smart agriculture, the sensor nodes or cameras collect enormous amounts of data that may be broken down into many different categories. The conventional methods of processing such a vast amount of data are insufficient, which is where big data analysis comes in.

Big data provides the capability to investigate very large datasets. It mitigates food security issues [46], provides predictive analysis and real time decision making, and it introduces new business models [178, 242]. All of these benefits can be attributed to the fact that the efficiency of the end-to-end supply chain in smart agricultural systems is improved.

Support Vector Machines (SVM) and Artifical Neural Networks (ANN) have been applied in order to integrate a big data platform in order to ensure the safety of the milk production chain [110]. The big data workflow in a smart agriculture system is depicted in Fig. 4 [46, 242]. It begins with the gathering of data at a variety of sensor nodes and finishes with the use of a variety of methodologies for data analysis, which can include both conventional and big data analysis.

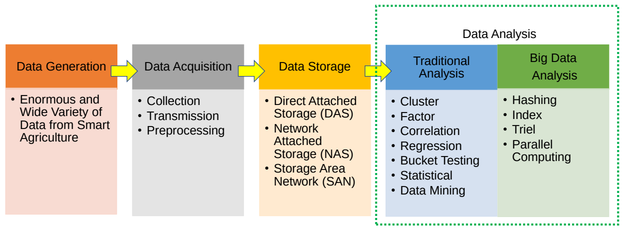



**Fig. 4** Big Data Work Flow in the Context of Smart Agriculture.

### 5.11 Challenges of AI

For sustainable, efficient, and automated agriculture, AI is a relevant choice. However, certain factors present challenges to employing AI in agriculture. The communication gap between the AI community and farmers is one of the major challenges. Multidisciplinary research can reduce this gap. Absence of regulations and policies is another challenge in applying AI. As sensors collect data from various regions, questions regarding data privacy and security come up. Cloud based solutions are also prone to cyber attacks. For edge-AI solutions, processing and computation of data is done locally. It reduces the chance of various attacks and solves the data privacy and regulation problem.

### 5.12 Technical Malfunction

Technical malfunction can impact a system negatively. Damaged sensors can wrongly sense data and errors can occur during decision making. It eventually can cause huge losses. For example, if the sensors in a crop field are damaged by hail, they sense wrong moisture data. As a result, the irrigation system may not work properly.

### 5.13 Lack of Initial Capital Investment

Establishing new technologies in the cropland needs huge initial capital investment. However, in developing countries, where farmers have very thin profit margins, large capital investment is not a viable option. It stalls the extensive use of technologies in agriculture.

### 5.14 Unavailability of Uniform Standards

There is no uniform standard across the globe for smart agriculture solutions. It makes the solutions complex and expensive. A uniform standard is needed worldwide [8].

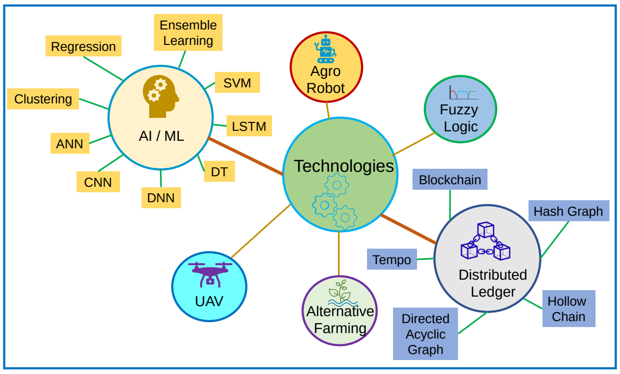
These aforementioned challenges pose significant bottleneck in implementing IoAT systems at various levels. The majority of them are common to any IoT system. However, each IoT system is impacted by these challenges at different degrees. For example, for IoAT system connectivity, huge amount of data generation, and awareness of the farmers about the available state-of-the-art technologies are major barriers in modernizing agriculture. Theses challenges must be conquered in order to assure increased efficiency and maximized profits.

## 6 Technologies for Smart Agriculture

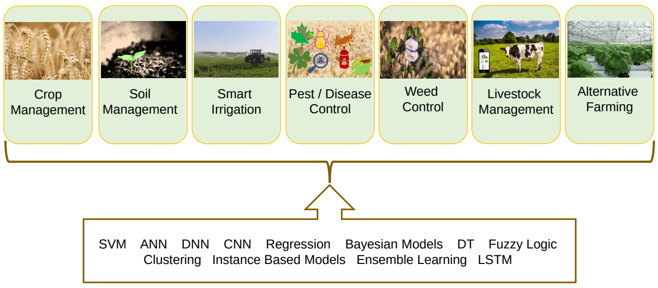
In 2021, when the world was struggling through the pandemic, a digital and sustainable ecosystem was welcomed by the world's industry sectors. *Industry 5.0* arrived with digital transformation. The relationship of "human" and "machine" is re-defined. *Industry 5.0* speeds up the advent of *Agriculture 5.0*. Two main technologies, (1) artificial intelligence (AI) or machine learning (ML) and (2) distributed ledger technology (DLT), along with other technologies mentioned in Fig. 5 will guide this transition from *Agriculture 4.0* to *Agriculture 5.0*.

### 6.1 Artificial Intelligence and Machine Learning

Machine intelligence that resembles human intelligence is referred to as artificial intelligence (AI). Progress in AI/ML technologies has shown great potential in variety of industries and research domains e.g., marketing [213], computer vision [141], multimedia forensics [139, 142, 144], healthcare [99], social media fake




(a) Technologies in Smart Agriculture.




(b) AI Tools for Smart Agriculture [122].

**Fig. 5** Various Technologies for Smart Agriculture.

image and video detection [140,143], gaming [167,209], autonomous cars, and farming.

When used in agricultural applications, AI increases the efficiency of agricultural systems. Fig. 5(b) shows various AI tools applied in agriculture. These tools from different publications are being used in various areas of agriculture, as discussed in Table 2.

Varied AI technologies are being proposed based on the location of the computation. Research is ongoing to create deep neural network models with higher accuracy and fewer training parameters for edge AI initiatives, where the AI model operates on the restricted resource embedded system itself [137]. MobileNet [89], SqueezeNet [93], and EfficientNet [218] are examples of networks that execute depth wise convolution, data down sampling, and uniform model scaling down, respectively. The DNN size is reduced via quantization [47,101,247,257] and pruning [23,77,81,86,152,248,250]. The right hardware is just as crucial as the right algorithms.

AI has the potential to revolutionize the way we think about agriculture, making it possible for farmers to accomplish more with less work while also offering a variety of other benefits. However, artificial intelligence is not a stand-alone technology. It can serve as a bridge between traditional farming and the next stage of agricultural innovation. It collects and evaluates large amounts of data on a digital platform, determines the most effective course of action, and even executes that course of action when integrated with other forms of technologies. It facilitates improved decision-making, reduces the cost, limits the use of fertilizers and pesticides, brings higher profits, improves harvest quality and yield, monitors weather and soil health, and provides faster and accurate solutions from smart irrigation to vertical farming.

## 6.2 Distributed Ledger Technology

Distributed ledger technology consists of distinct nodes that help record, share, and synchronize the data transactions in their respective electronic ledgers instead of using central storage servers. Some examples of this technology include blockchain, DAG, Holochain, Tempo, and Hyperledger Fabric. Some ledger technologies, limitations, and applications are discussed here.

### *6.2.1 Blockchain*

One of the recent digital technologies which has proved disruptive in the field of finances [40, 159] eliminating the need for centralized authorities and managing digital assets is the blockchain. Even though starting as financial solution, the blockchain has shown potential use cases in many industries like Real-time Secure IoT systems [94, 204], Smart Governance applications [75, 87], Digital Asset Copyright technologies [245, 252], Smart Healthcare [26,30,181] including Smart Agriculture and many other industries. Blockchain characteristics like hash linked data structure, cryptography verification, consensus based transaction processing helps in removing centralized authorities and provides more data security in an untrusted P2P network. IoT is another technology which has been a driving factor for smart agriculture systems in which using the IoT to make the farms climate resistant and also helps in achieving predicted yield even in case of environmental parameter fluctuations [127]. IoT three layered architecture consists of sensing layer, edge layer and cloud layer. Edge devices which are responsible for collecting data from sensing layer and process them form Edge Data Centers (EDC). They form a P2P network of EDCs to communicate and collectively work to process the information [180]. This machine-to-machine communication happening between EDCs can be made more secure and robust to network attacks by implementing the blockchain as solution. The relevance between application of blockchain in smart agriculture can be seen clearly in Fig. 6. Different applications of blockchain in smart agriculture can be seen in Table 3.

**Table 2** AI Technologies of Smart Agriculture.

| **Applications** | **Descriptions** | **Works** |
|---|---|---|
| Crop Management | Yield prediction, crop growth, damage estimation, and food supply chain researches come under crop management research. Varied AI/ML methods e.g., Support Vector Machine (SVM), Gaussian Naive Bayes, various artificial neural networks (ANN), regression models, and clustering have been used. | SVM has been used in [185] to count the number of coffee fruits in a plant branch, rice yield prediction in [214], and in [198] to detect green immature citrus fruit. Gaussian Naive Bayes has been used to estimate cherries in a branch [21]. To estimate biomass of the grassland [17], to predict wheat [169], corn and soybean [109], corn [226], rice in hilly area [97], cotton [138, 253], wheat [190], maize [205], tea [211], general crop [53] yields, crop yield from soil parameters [124], crop nutrition disorder detection [212], and effect of crops on soil salt and water content [54]. Clustering is used in [199] for tomato detection from UAM images. Crop growth monitoring is done in [120]. |
| Soil Management | Smart agricultural systems include soil property management, such as soil moisture, temperature, and nutrient content. It has two advantages: it increases crop output while also conserving soil resources [63]. However, the procedure is time-taking and expensive. Hence, a variety of low-cost and self-contained machine learning algorithms have been presented in order to develop a dependable soil management system [122]. Sensor data, satellite photos, and UAV images are commonly used as input to machine learning models. In predictive analysis, ANN, SVM, and autoencoders have been used. | For soil suitability evaluation, ANN and Multi-Layer Perceptrons (MLP) have been applied [236]. ML models have been used to forecast phosphorus in soil [59]. To extract geo-parcels from high-resolution photos, Deep Neural Networks (DNN) were used, while MLP was used to forecast phosphorous content. The water retention capacity of soil in Brazilian coastal areas has been predicted using a radial basis function neural network [42]. Soil moisture may also be predicted from UAV-taken pictures using Boosted Regression Trees (BRT) [24] and ANN [25]. SVM was used to estimate the health and condition of soil moisture sensors, as well as the stage of degradation using Naive Bayes classification [96]. From satellite pictures, autoencoder and SVM have been used to predict soil salinity [115]. |
| Smart Irrigation | Smart agriculture systems include water management as a key component. Climate change is causing changes in rainfall patterns around the planet. Evapotranspiration is an important factor to consider when evaluating water supplies. In smart water management, a variety of AI technologies have been used. | In a crop field, deep reinforcement learning was applied for smart water management [39]. The water required for greenhouse organic crops was calculated using a multiple linear regression method, and then water valves were automatically operated using a LoRa Point-to-Point (P2P) network [44]. In [161], a study in Dehradun, India was used to suggest an ANN method for predicting evapotranspiration. Daily evapotranspiration has been predicted using ANN and the Penman-Monteith equation [22]. In an Edge-Fog-Cloud environment, a smart irrigation system based on Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models has been presented [52]. Another LSTM based irrigation system has been presented in [108] for precision agriculture. A neuro-drip irrigation system's spatial water distribution was predicted using ANN in [85]. |
| Pest/Disease Control | Disease, pest, and weed control are required to get the highest yield from an agricultural field. An automated system can help save time and expense. AI approaches are being proposed in several papers from this standpoint. | In the recent decade, rule-based systems [28,29,132,173,196] were developed, which were followed by Fuzzy Logic based systems [177, 206, 222, 228]. Various ANN have been used to detect various pests in a crop field [126] or to detect diseases in different crops [69,79,107,210]. For example, a channel–spatial attention module, incorporated with a backbone CNN and a Region Proposal Network (RPN), has been utilized for detecting different pests in a crop field [126]. Apple leaf disease is identified in [100] using the GoogleNet Inception network and Rainbow concatenation and in [145] using Mask R-CNN. For identifying pests in a tea plant, an incremental back propagation network was used with Correlation-based Feature Selection (CFS). The pest Tessaratoma Papillosa was localized using the CNN-based object detection model YOLOv3, and pest incidence was predicted with 90% accuracy using LSTM analysis of environmental data [45]. |

*Continued on next page*

Table 2 – Continued from previous page

| Applications | Descriptions | Works |
|---|---|---|
| | | Anthrax on apple surface in an apple orchard was also detected using the YOLOv3 and YOLOv3-Dense models [239]. Single Seed Descent (SSD) has been shown to have an accuracy of 84% in detecting pests and 86% in classifying pests [134]. Using k-means clustering and a correspondence filter, pest detection and recognition were achieved [68]. In crop disease identification, various CNN-based models have been employed in [146,168,225]. Google object detection API with customized convolutional neural network has been used to detect good and bad coffee beans [91]. Recently, in [147], YOLOv5 and YOLOv8 have been used to detect pear, rice and wheat diseases in real time. In [58], the authors explored different light-duty computing platforms in IoAT-edge AI for plant disease detection. |
| Weed Control | Weed has a negative impact on yield. Weed control is thus another crucial aspect of smart agriculture. Weeds can be a nuisance at times. It's difficult to tell them apart from crops. Artificial intelligence (AI) was first used in weed management in the early 2000s. | Hebbian synaptic modification was used with ANN to differentiate weeds from crops [14], and the accuracy gained was acceptable given the hardware present at the time. In [172], YOLOv3 was employed for less expensive weed management. To detect weeds, researchers used Counter Propagation (CP)-ANN with multi-spectral pictures [171] and a combination of auto encoder and SVM with hyper spectral images [170]. SVM was used in detecting weeds in grassland cropping in [35]. [111] uses a semi-supervised method to detect weeds. |
| Livestock Management | Animal welfare and livestock production have both benefited from AI/ML strategies in livestock management [122]. | Authors in [60] used bagging ensemble learning for cattle, decision tree and C4.5 algorithm for calf [176], and Gaussian Mixture Models for pigs well-being [135]. AI aids in the optimization of livestock production efficiency. The work in [51] employed an ANN with back propagation to predict cattle rumen fermentation patterns from milk fatty acids. Faces of pigs were identified with 97 percent accuracy using CNN in [82]. SVM has been used to discover and warn about problems in egg production for commercial hens [154], to estimate cattle weight trajectories for evolution [20], and to predict beef cattle skeletal weight [19]. In a robotic cow farm, ANN with Bayesian Regularization were utilized to forecast quality milk output and lower cow heat stress levels [73]. In [165], a fully connected neural network was utilized to forecast cow illnesses. |
| Alternative Farming | Greenhouse farming and hydroponics are examples of alternative farming. In those systems, machine learning and deep learning approaches are employed to provide superior and more accurate manage with less manpower. | Fully linked ANN and Root Mean Square Error (RMSE) are used to anticipate greenhouse air temperature [48]. ANN has been used to increase yield and growth for tomato [62] and basil yield in the greenhouse [166], greenhouse gas emissions and energy usage of wheat [114], and watermelon yield [157]. The humidity and temperature of a solar powered greenhouse were predicted using a Recurrent Neural Network (RNN) with back propagation [88]. RNN-LSTM has been used for climate prediction in [105]. In hydroponic systems, ANN and Bayesian Networks have been employed to forecast the required job [136]. |

#### *6.2.2 Directed Acyclic Graph (DAG)*

A Distributed Ledger with a directed acyclic graph (DAG) is used in IOTA Tangle, where each point represents a single transaction, and the arrows are authorizations. Each individual transaction is directed toward the previous parent transactions and is responsible for approving child transactions directly or indirectly as in Fig. 7. The IOTA Tangle is immutable by its novel consensus mechanism. Every transaction has a small Proof of Work (PoW) activity for consensus, making it impossible for the hacker to attack. An algorithm called Random Walk Monte Carlo is used for authentication. The Tangle grows and moves forward to increase the

**Table 3** Blockchain Technologies in Smart Agriculture.

| Applications | Description | Works |
|---|---|---|
| Secure Real-time Data Sharing | Data security and privacy is one of the important issues in IoT systems, robust cryptography is not a feasible solution considering resource-constrained IoT devices. Injection of false data and Denial-of-Service (DoS) are most common security attacks on IoT systems. There is a need for robust mechanism to share data between P2P network formed by EDC's | Blockchains as secure data sharing systems in smart agriculture is proposed in [129,200,244,256]. A robust identity management system is proposed in [244] which will make use of private blockchain and prevent DOS attacks. A combination of SDN and blockchain networks is proposed in [200] which provides minimal overhead and provide robust security in agriculture systems. Work in [256] proposed an ethereum platform based system and made use of Practical Byzantine Fault Tolerant (PBFT) consensus mechanism. Key management system to securely share data is proposed in [129] which provides a secure, reliable and scalable key-management system which can be adapted in smart agriculture with numerous number of sensing nodes. The work in [31] proposes a distributed ledger based crop monitoring system which is a scalable blockchain environment in real-time data sharing and equip participating entities with decision support tools. |
| Community Farming and Local Markets | Community farming helps in sharing key data like weather, crop disease or product demand which can help as means for farmer to understand which crop should be cultivated. Local markets not only make fresh produce available to the consumer directly but also remove middle-men involved in the supply chain in order to maximize the profits of farmers. Providing these two can make farming a profitable venture and lead more individuals to participate in irrigation thereby increasing yield and provide food security. | A blockchain framework has been proposed which is implemented using Ethereum platform and can help in adapting ethical supply chains into farming [174]. Thereby, realizing profits to the farmers. |
| Supply-Chain Traceability | Food supply chains is a major component of Agriculture-CPS systems which enables the food products available to all the corners of the world and also leverages collective working of organizations which are geographically placed apart. Due to involvement of multiple entities and complex interactions between them, supply chain has become more complex and can lead many issues like Difficulty in tracking and tracing, processing delays leading to degradation of produce, resolving conflicts, lack of consumer confidence and recalls which increases unnecessary wastage of produce. | Hyper ledger Fabric based systems are proposed in [133,243] as a case study to check the blockchain based supply chains. RFID has been integrated with blockchain systems to provide a transparent supply chain solution in [221]. A smart contract based solution for solving Single Point of Failure (SPOF) in centralized systems like ERP is proposed in [106]. The work in [32] proposed a system which uses ethereum platform to build a transparent supply chain for organic foods to increase customer confidence while consuming. A method integrating EPIC and blockchains is proposed by [123]. |
| Farm Insurance | Farming yield majorly depends on the environmental parameters and climatic changes. This can lead to financial in-stability of the farmers which may drive awsy many people from practicing farming as livelihood. Farm insurance is a financial setup where farmers will pay a fixed premium to a company and will be compensated with insured amount in case of damage to the crop from adverse climatic changes. These farm insurance companies need to assess the damage on the crop by following certain indexes pertaining to the weather parameters, blockchain can help in securely assess such parameters and provide a holistic indexes for computing the compensations. | A fraud detection and avoidance system for farm insurances based on blockchain is proposed in [160]. A drought based insurance payout system is proposed and implemented in [162]. Authors of [16] proposed a blockchain based solution which leverages smart contracts on ethereum and hyperledger fabric platforms to design a insurance service system. |

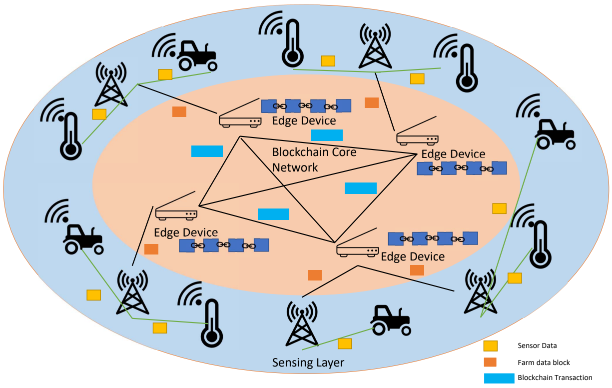



**Fig. 6** IoT Network and Blockchain in Smart Agriculture.

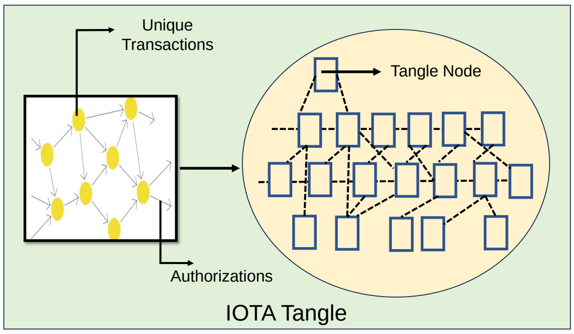



**Fig. 7** IOTA Tangle Architecture

weight to reach the consensus, and the transactions with light weight are orphaned and are not involved in the new consensus. Tangle can be more advantageous than blockchain for evading high fees, energy, and double spending vulnerabilities [230]. It has built-in two-layer solutions with MAM and STREAMS for data security and authentication and works on the principle of cryptography. It supports the concept of zero-valued transactions and can work with off-chain storage to skirt higher data volumes on the tangle [230].

### *6.2.3 Limitations of Blockchain*

Blockchain has clearly shown many applications which can benefit the different smart agricultural operations but still adapting such technology in large scale and resource constrained smart agriculture systems is difficult. Blockchains as such consume large amounts of power and need large computational tools which is a major problem in IoT based smart agriculture systems. Hence, blockchains should be modified either by the structure or mechanisms in order to make them more feasible, reliable and scalable solutions for smart agriculture. A lightweight consensus mechanism Proof-of-Authentication is proposed in [179] which is IoT friendly and consumes much lower power compared to other consensus protocols used in leading blockchain platforms. Another problem in implementing blockchain technologies in smart agriculture is the amount of data generated from the IoT networks, as the farms generate large amounts of data points will be collected every minute and analyzed. There is large constraint on blockchains on the amount of data that can be included in each block. Hence, efficient distributed off-chain solutions are on the rise. One such application which makes use of off-chain storage is the Inter-Planetary File System (IPFS) along with ethereum platform and leveraging smart contracts is proposed in [229]. Access management is also a major issue, a method to provide multi-level data access policies which is scalable and can be adapted into smart agriculture systems can be seen in [36].

Taking advantage of blockchain features of the incentive layer, an application for saving resources while farming is developed. This layer defines the minimum amount of transaction fees needed to perform actions on the blockchain. However, the paper proposes a novel idea using the same transactions as incentives to the farmers in the form of insurance once the electricity and water units are equaled to a prior condition to minimize carbon footprint, thus enhancing smart agriculture features through robust security [231]. To improve the security features for integrity and authentication and avoid central and blockchain limitations, IOTA Tangle is implemented to send the smart agricultural data in a secured method [230].

## 7 Datasets for Smart Agriculture Research

Smart devices are used in precision farming to collect data and analyze the yearly crop yields, supply chain transactions, and livestock management. The data stored using modern techniques in smart agriculture is then utilized for further research to ensure the availability of resources for future generations. Table 4 gives different datasets of various formats that were used for study in the current survey paper.

### 7.1 Crop Yield and Production

Many different sensors are used for gathering data on crop conditions, acreage, and yearly yields of the land. The total amount of crop yield data can be estimated by the ratio of the amount of produce to the harvested area, which is in terms of tonnes per hectare. The annual reports that the USDA gives have information regarding the yield, production estimates, costs in agriculture, livestock, plants, and agriculture census. The

**Table 4** Datasets for Smart Agriculture.

| Dataset Format | Dataset Purpose | Source | Link |
|---|---|---|---|
| .php | Crop Yield & Production | USDA & NASS | https://www.nass.usda.gov/Charts_and_Maps/ |
| .gis | Crop Condition & soil moisture | Crop-CASMA | https://nassgeo.csiss.gmu.edu/CropCASMA/ |
| .jpg | PlantVillage | Mendeley Data | https://data.mendeley.com/datasets/tywbtsjrjv/1 |
| .mdb | Soil Health & characterization | NCSS | https://new.cloudvault.usda.gov/index.php/s/7iknp275KdTKwCA |
| .php, .txt | Pesticide use in agriculture | USGS | https://water.usgs.gov/nawqa/pnsp/usage/maps/ |
| Tableau | Water use in Agriculture | USGS | https://labs.waterdata.usgs.gov/visualizations/water-use-15 |
| .jpeg | Groundwater nitrate contamination | USGS | https://prd-wret.s3.us-west-2.amazonaws.com/assets/palladium/production/s3fs-public/thumbnails/image/wss-nitrogen-map-us-risk-areas.jpg |
| .png, .pdf | Disaster analysis | USDA & NASS | https://www.nass.usda.gov/Research_and_Science/Disaster-Analysis/ |

USDA: U.S. Department of Agriculture. NASS: National Agricultural Statistics Service.

NCSS: National Cooperative soil Survey. USGS: U.S.Geological Survey.

prices, labor values, and production values change monthly and annually and are presented in [13].

### 7.2 Crop Condition and Soil Moisture

The crop yield can depend on many different factors, one of which is soil moisture. With humidity sensing, water availability, predicting weather disasters, and planning yearly crops can be performed easily. For different stages of agriculture to be realized quickly, soil data plays a vital role for the farmers to act accordingly. The NASA and USDA-NASS collaboratively have developed an application that collects the data in Geographic information system mapping format (.gis) [227], called Crop-CASMA, which is a web-based geospatial application used to measure the moisture of the soil and cropping conditions. The data of the moisture level and the state of the crops is given in Fig. 8(a).

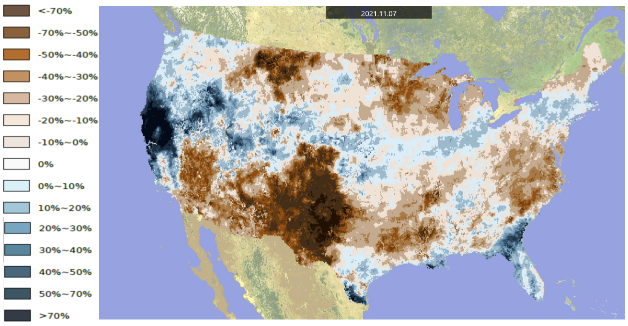
### 7.3 Plant Diseases

Infections and diseases can change the core genetics and nutritions present in the crops, which can be harmful to consumers. Each plant species has its unique pattern and condition. Specific datasets of different plant infections is available in [3,92]. Fig. 9(a) and Fig. 9(b) show the images of healthy crops and crops infected with diseases. These images are used for training and testing of applications for predicting crop sickness to improve the harvest yield and productivity. Sample pomegranate images of different grades and qualities from the Pomegranate Fruit Dataset are shown in Fig. 9(c) [7].

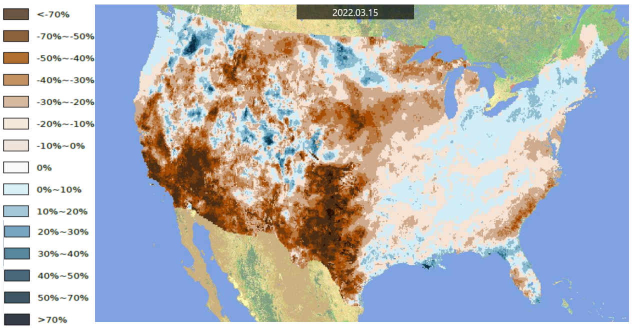
### 7.4 Soil Health and Characterization

Survey conducted to know soil characteristics explain the features and properties of the soil. Farmers, engineers, and land agents are the end gainers of the soil survey data.

The classification of the soil database is provided by the National Cooperative Soil Survey (NCSS) with a pedon number associated with each report. The pedon gives a three-dimensional structure of the soil and explains the components present inside the ground. The properties of the earth like phosphorous, sand, water content, rock fragments, salt, pH levels are collected from the primary data characterization. Each report can be downloaded directly from the site in the form of graphs and text format by giving key details of country, state, and county.




(a) Dated November 07, 2021




(b) Dated March 18, 2022

**Fig. 8** Crop Condition and Soil Moisture in the United States [227].

### 7.5 Pesticide Use in Agriculture

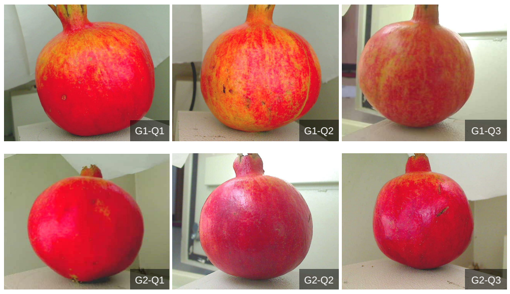
For controlling weeds, insects, and fungi, many pesticides are used, but excessive usage can pollute groundwater and kill other microorganisms that are necessary for the health of the soil. The USGS creates a database in the form of tables, graphs, and maps annually for showing the amount of pesticide used in farming [217]. The map gives a more detailed view of how much of the pesticide is used on the agricultural land in pounds per square mile, and graphs illustrate the estimated usage of fertilizers in millions of pounds each year.

### 7.6 Water Use in Agriculture

For farming livestock and crops, water plays an important role. Water is available for agriculture from both surface and groundwater [215]. Rivers and lakes are the primary sources for forming surface water, whereas groundwater resides in the sand cracks, rocks, and soil. The data for water usage are collected and updated every five years by the USGS in terms of billion gallons per day. The data collected illustrates that most of the water usage is in agriculture and industry [216].

(a) Healthy Plant Leaves - Potato [3], Peach [3], and Chinese Cabbage [2] (From Left to Right)

(b) Infected Plant Leaves - Potato [3], Peach [3], and Chinese Cabbage [2] (From Left to Right)




(c) Pomegranates of Different Grades and Different Qualities. G represents Grade and Q represents Quality [7].

**Fig. 9** Sample Images from Various Plants and Fruits Datasets

### 7.7 Groundwater Nitrate Contamination

Nitrate is an oxidized form of nitrogen that helps in growing plants and crops. It is a compound that can be found naturally in the soil, but this compound can decrease if the land is extensively farmed. In order to increase the nutrients in the earth, different artificial nitrogen chemicals are used for growing crops. These nitrogen fertilizers can be harmful when they go inside crops, livestock, water, and groundwater. The USGS has designed a model to analyze how much groundwater is contaminated through the nitrate [197].

### 7.8 Disaster Analysis

As the global temperatures, changing landscapes, and uncertain risks increase, the agriculture sector is facing adverse effects and threats. The disasters should be analyzed and estimated before they occur because the farmer has to be prepared for planning the crops accordingly. USDA and NASS are conducting research studies for disaster analysis in real-time. Most of the datasets are collected using sensors and geospatial methods to study the time when the disaster arises [4]. Sentinel-1, a Synthetic Aperture Radar is a modern tool that is used for studying and monitoring floods [38].

## 8 Smart Agriculture Open Research Problems

The open research problems of *Agriculture 4.0* and *Agriculture 5.0* are discussed in this section. Depending on the research objective, we can divide them into two major subgroups.

### 8.1 Technology Perspective

As aforementioned in Section 5, smart agriculture faces a number of implementation challenges. These issues must be addressed by the adaptation of existing and future technologies. Most smart agricultural AI models were cloud-based, cloud-edge-based, or cloud-fog-edge-based up until now. The shift in computing paradigm has been aided by hardware advancement. According to [203], adding intelligence to IoT devices is the new trend. Network availability, latency, and bandwidth are no longer obstacles in the operation of a viable, uninterrupted agriculture system. This opens up a new path to researches. The use of edge AI in smart agriculture is a huge deal that will become increasingly popular in the coming years. Fig. 10(a) depicts a variety of open research challenges in the context of technology. The following fields of study offer a lot of promise:

- Exploring tinyML devices with low power and low latency and solar powered devices.
- Low computing methods for IoT devices.
- Extreme temperature operable sensors.
- Data compression techniques.
- Quantization and pruning methods for deep learning models.
- Research on unsupervised and semi-supervised learning.
- Real time data processing and computation.
- More public dataset generation.
- UAV taken images accessible by the public.
- Thermal and Infrared image dataset.
- Annotated dataset for image segmentation.

These aren't the only research areas available. Other topics to work with include blockchain-based data privacy and integrity, as well as service-based smart agriculture applications, hardware security include the following:

- Blockchain-enabled IoT applications that emphasize immutable data storage techniques.
- Optimizing computing capabilities, lowering design time, and increasing efficiency are on the list too.
- Research on PUF, a hardware signature [102, 121], is a significant area of study.
- Vulnerability of PUF to environmental factors such as rain, herbicides, fertilizers, and chemicals.
- Reliability and tamper resistance of PUF.

### 8.2 Network Perspective

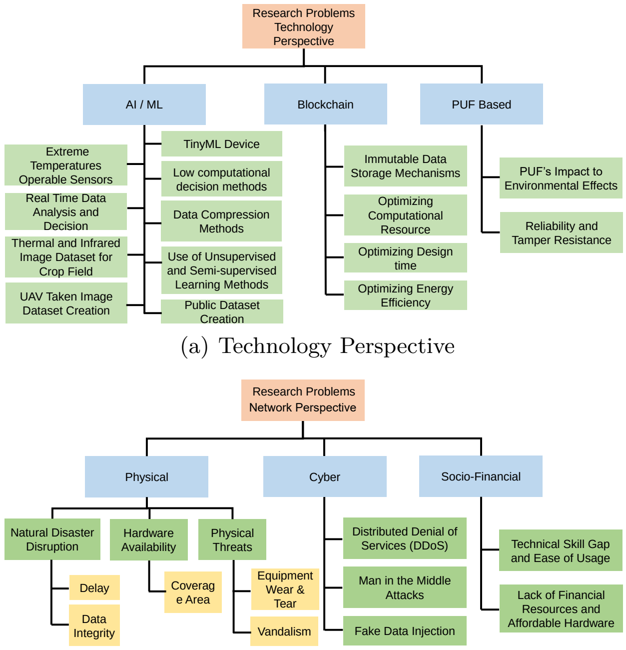
Network connectivity of smart agriculture is a critical component that uses various ICT to connect remote equipment, devices, and facilitates data transfer. Various security vulnerabilities have arisen as a result of developing unprotected network layer protocols for restricted resource IoT devices. Fig. 10(b) shows a classification of research difficulties from network perspective needs to be addressed including the following:

- Research on alternative networks in case of natural disasters.
- Methods for real time data processing even if the network is congested.
- Robust and resource friendly data privacy and security techniques.
- Minimize the blind spots by expanding the coverage area of the network.
- Cost effective methods for easy maintenance of instruments.
- Preventive approaches to counteract physical damages of the devices by adversaries [249].
- Improved network routing algorithm to avoid various network attacks.
- Efficient encryption and hardware authentication algorithms.
- Making troubleshooting mechanisms simple.
- Affordable equipment.

## 9 Conclusions

We regard "Let food be thy medicine" more than ever in today's environment since good food strengthens our immunity. Agriculture, food security, and the food supply chain have all become more vital in recent years. This article provides a comprehensive overview of current smart agriculture research efforts. It covers everything from the latest technological advances to open research concerns in this field. The authors anticipate that this paper will provide a broad overview of smart agriculture technology, challenges, and research issues.

Traditional agriculture has been changed into a smart, intelligent, and automated agriculture as a result of




(a) Technology Perspective

(b) Network and Communication Perspective

**Fig. 10** Open Research Problems of Smart Agriculture.

technological breakthroughs and the rapid rise of ICT. By implementing sustainable, green farming, decreasing the use of pesticides and fertilizers, and maximizing the use of natural resources, smart agriculture decreases the carbon footprint. It will also address other issues such as climate change and diseases such as cancer.

Agriculture 5.0 [194] will arrive in the agricultural industry soon. This will increase production while also ensuring the system's long-term viability. The same trend will be seen in developing countries as in wealthy countries. Humanity will welcome the production and delivery of food in a way that is both economically and environmentally efficient like never before [70].

## Compliance with Ethical Standards

The authors declare that they have no conflict of interest and there was no human or animal testing or participation involved in this research. All data were obtained from public domain sources.

## Acknowledgments

An extended version of this paper has been archived in [150].

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