EVERYTHING YOU WANTED TO KNOW ABOUT SMART AGRICULTURE

A PREPRINT

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ABSTRACT

The world population is anticipated to increase by close to 2 billion by 2050 causing a rapid escalation of food demand. A recent projection shows that the world is lagging behind accomplishing the "Zero Hunger" goal, in spite of some advancements. Socio-economic and well being fallout will affect the food security. Vulnerable groups of people will suffer malnutrition. To cater to the needs of the increasing population, the agricultural industry needs to be modernized, become smart, and automated. Traditional agriculture can be remade to efficient, sustainable, eco-friendly smart agriculture by adopting existing technologies. In this survey paper the authors present the applications, technological trends, available datasets, networking options, and challenges in smart agriculture. How Agro Cyber Physical Systems are built upon the Internet-of-Agro-Things is discussed through various application fields. Agriculture 4.0 is also discussed as a whole. We focus on the technologies, such as Artificial Intelligence (AI) and Machine Learning (ML) which support the automation, along with the Distributed Ledger Technology (DLT) which provides data integrity and security. After an in-depth study of different architectures, we also present a smart agriculture framework which relies on the location of data processing. We have divided open research problems of smart agriculture as future research work in two groups - from a technological perspective and from a networking perspective. AI, ML, the blockchain as a DLT, and Physical Unclonable Functions (PUF) based hardware security fall under the technology group, whereas any network related attacks, fake data injection and similar threats fall under the network research problem group.

Keywords Smart Agriculture, Internet-of-Things (IoT), Cyber-Physical Systems (CPS), Agirculture Cyber-Physical Systems (A-CPS), Internet-of-Agro-Things (IoAT), Physical Unclonable Function (PUF), Distributed Ledger Technology (DLT), Blockchain

1 Introduction

The world population is anticipated to reach 9.7 billion by 2050 and could reach 11 billion by the end of this century [1]. Given these projections, it is anticipated that worldwide food consumption will increase at a rapid pace. The needed increase in food production to serve the future population is a tremendous task. Escalating food supply production is only possible through sustainable and smart agriculture. A goal has been set to end hunger all over the world by 2030. But currently, we are not in a trajectory to reach that goal [2, 3]. Today 800 million people are undernourished worldwide. Increased population plays a significant role in this issue. More people means more food. By 2050, 70% more food production is needed to adequately feed the world's population [4]. A number of other factors are aggravating this situation:

- Urbanization is changing food habits. People are consuming more animal protein. In 1997-1999 annual animal protein per capita consumption was 36.4Kg which will increase to 45.3Kg by 2030.
- Natural resources are being depleted. Farming lands are turning into lands unsuitable for agriculture. 25% of the current farming land is highly unsuitable and 44% is moderately unsuitable. Water scarcity has turned 40% of the farming land into barren land.
- Deforestation for urban expansion and new farmland is rapidly depleting groundwater.
- Over farming is leading to short fallow periods, lack of crop rotation, and livestock overgrazing causing soil erosion.
- Climate change is happening rapidly. It is affecting every aspect of food cultivation. Over the past 50 years, greenhouse gas emissions have doubled which results in unpredictable precipitation and increased occurrence of droughts or floods.
- Food wastage is another contributing factor. 33% to 50% of the food produced is wasted across the globe.

To alleviate these issues, the food and agricultural industries welcome "Agriculture 4.0", a green, smart revolution with science and technology at its core. Fig.1 shows an overview of smart agriculture.

If we travel back through the industrial revolution, we see that it actually started in the Neolithic and Copper Ages when ancient people used wood and rock as instruments and later adopted metals for farming. But *Industry 1.0* started with the use of the steam engine. Mass production and use of electrical energy initiated *Industry 2.0*. *Industry 3.0* comes with automation and use of information technology whereas *Industry 4.0* connecting the machines and nodes in cyber physical systems through AI, Big Data (BD), the Internet of Things (IoT), robotics, etc. [5]. A parallel agricultural revolution also happened - starting with indigenous tools in *Agriculture* 1.0, use of tractors and fertilizers in *Agriculture* 2.0, decision and monitoring systems in *Agriculture* 3.0 and smart farming or smart agriculture in *Agriculture* 4.0 [5]. Agriculture 4.0 is defined by the amalgamation of various technologies, e.g. the IoT, AI, the blockchain, the use of Unmanned Aerial Vehicles (UAV), nanotechnology, and robotics, as shown in Fig. 2.

The rest of this survey is organized into eight sections. Section 2 presents the importance of smart agriculture. Section 3 presents the smart agriculture architecture. Internet-of-Agro-Things (IoAT) based Agriculture Cyber Physical Systems (A-CPS) is discussed in Section 4. Various applications of smart agriculture are described in Section 5. Challenges the industry faced are depicted in Section 6. Section 7 describes different technologies adapted in smart agriculture, whereas Section 8 discusses available datasets in the agricultural industry. Section 9 talks about the open research problems for the future and finally Section 10 concludes the paper. A list of acronyms used in the paper is appended at the end of the paper.

2 Smart Agriculture and Why Do We Need It?

Traditional agriculture with manual labor and low productivity is being transformed into sustainable, intelligent, efficient, and eco-friendly agriculture with the use of technologies such as those depicted in Fig. 2. Long established, old-world agriculture is transmuting to "smart" agriculture. New terminologies are emerging - "smart farming," "digital farming," "precision farming." "Smart Farming" is another name for "Smart Agriculture." In "Smart Farming" the focus is accessing data and applying those data to optimize a complex system towards increasing the quality standards and yield of the produce along with reducing human labor.

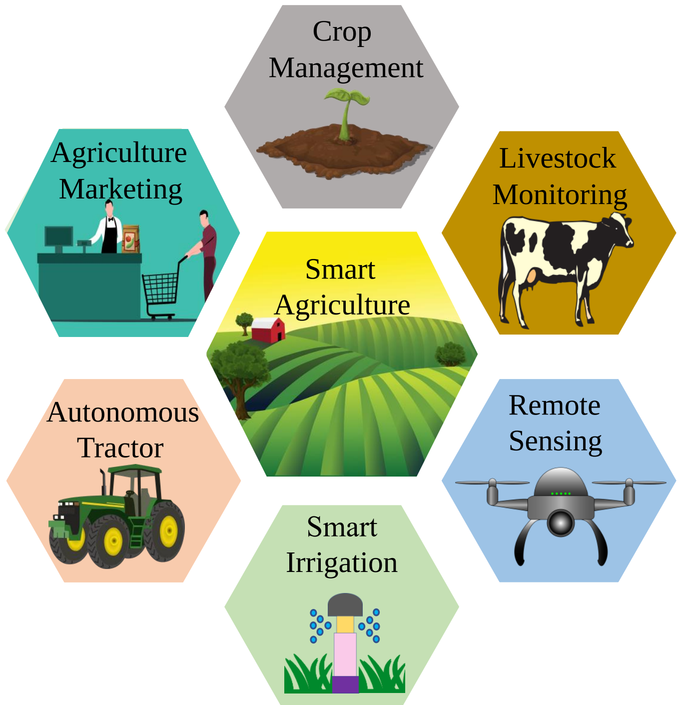


Figure 1: Smart Agriculture Overview.

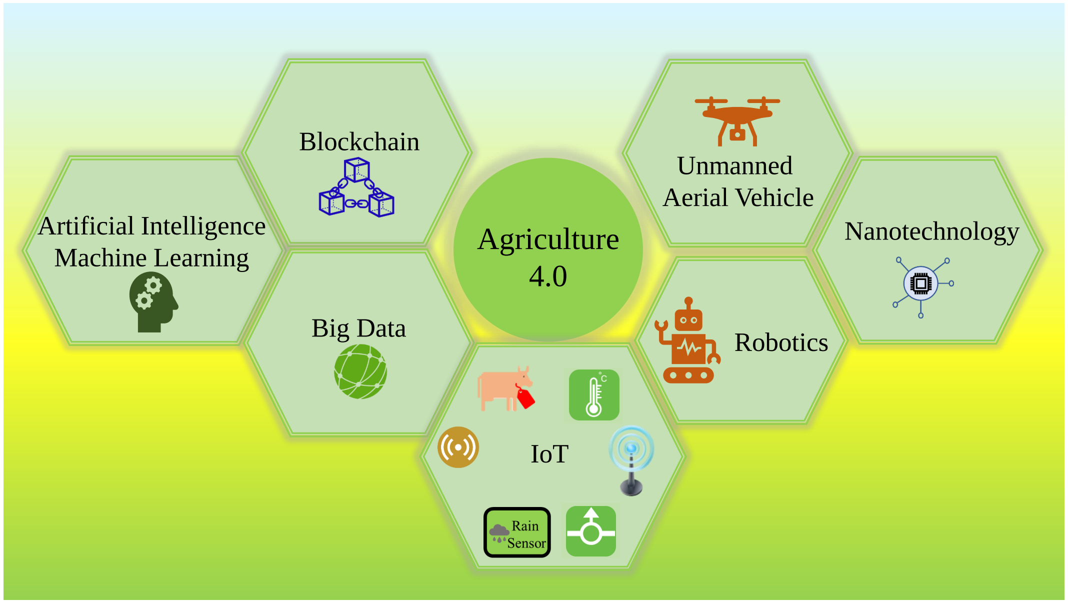


Figure 2: Elements of Agriculture 4.0.

"Precision Farming or Agriculture" and "Digital Farming" are mostly the predecessors of "smart agriculture" [6]. When the goal of farming is optimization, accuracy, and customized solutions for a particular field or crop with the help of different technologies, it falls under the label "Precision Farming or Agriculture." "Digital Farming" is the combination of these two. In this paper, we will discuss "smart agriculture" which addresses "Agriculture 4.0" and its future.

Fig. 3 shows the tremendous benefits of smart agriculture compared to traditional agriculture. They are:

- Water conservation.
- Optimization of the use of fertilizers and pesticides. As a result, produce are more toxin free and nutrient rich.
- Increased crop production efficiency.
- Reduction of operational costs.
- Opening up of unconventional farming area in cities, deserts.
- Lower greenhouse gas emissions.
- Reduced soil erosion.
- Real time data availability to farmers.

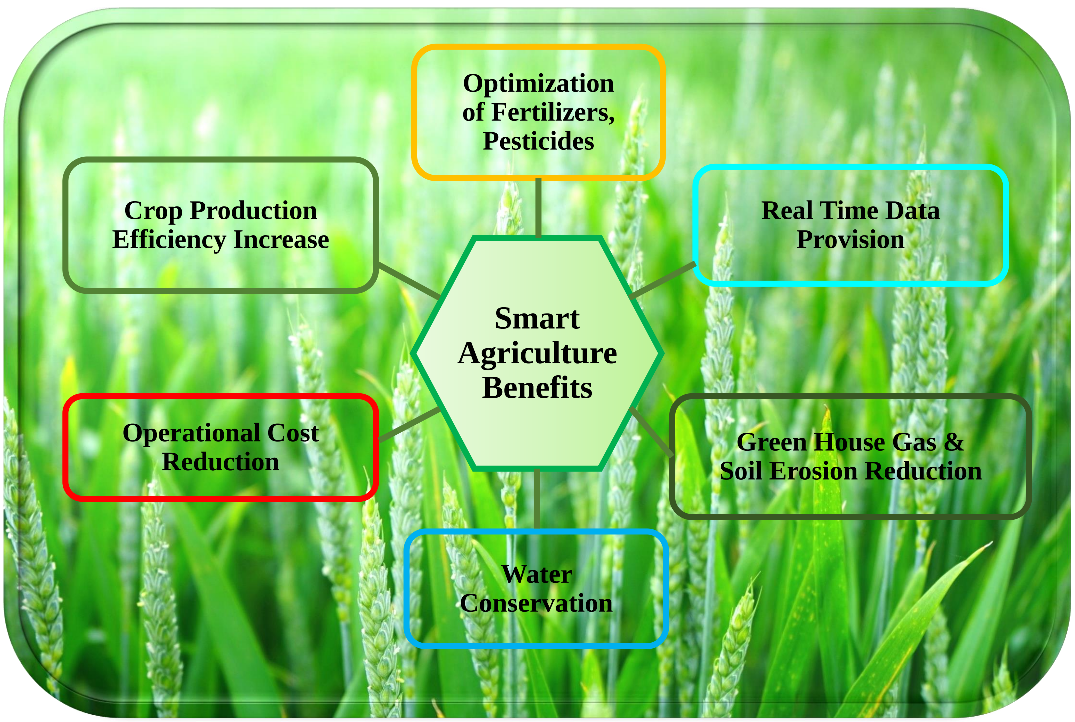


Figure 3: Smart Agriculture Benefits Over Traditional Agriculture.

3 Smart Agriculture Architecture

The IoT has been recently boosting the agricultural industry. Different technologies, protocols and standards are being employed. Depending on the application, the number of associated layers varies in the implementation architecture. Smart agriculture architectures with three layers [7, 8, 9], four layers [10, 11], five layers [12], six layers [13], and seven layers [14] have been presented in the literature. Different names and perspectives have been used in those architectures. We adapt a generic architecture, where layers are defined depending on the location (proximity to the occurrence) of their processing and how are they connected. This smart agriculture architecture is shown in Fig. 4.

We depict the architecture with three main layers. These layers are connected through two *connectivity layers*. We divide them in two sub layers as both connectivity layers connect different layers with different technologies. As the connectivity layer establishes a bridge among all the layers, it is the core layer of smart agriculture architecture through which all the layers work in sync with each other.

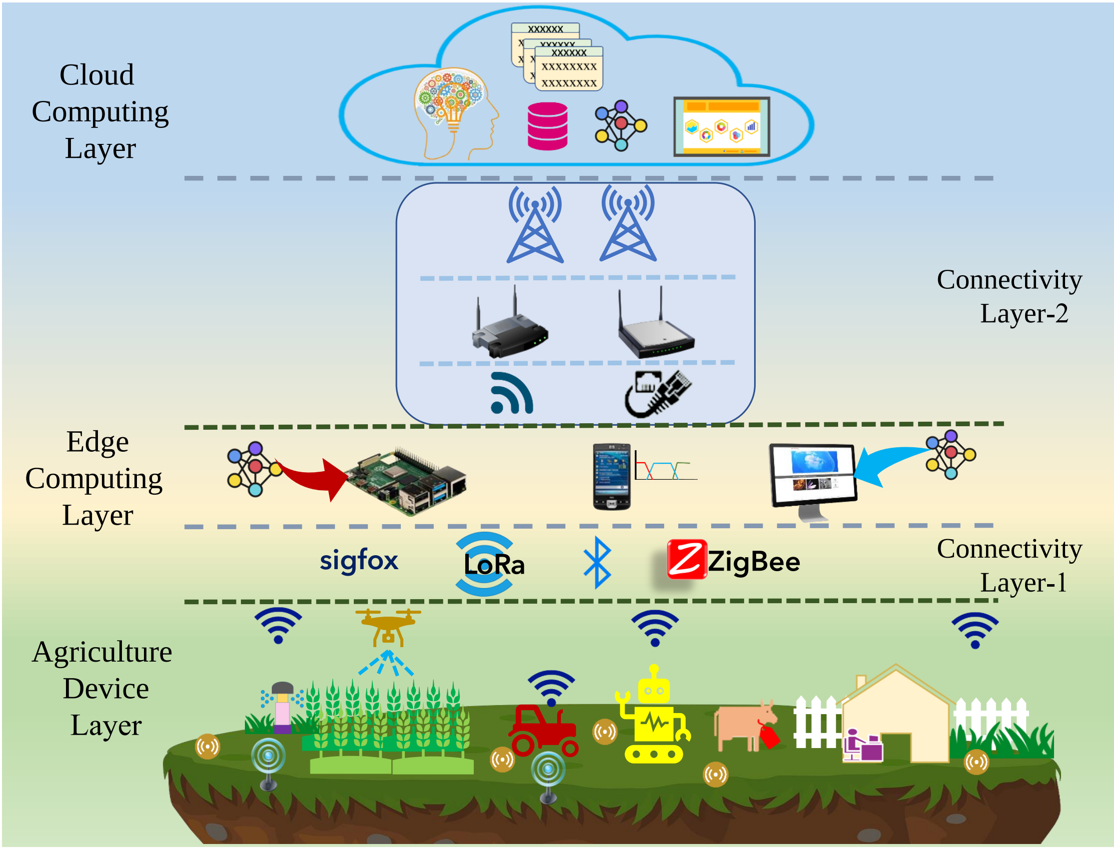


Figure 4: Architecture of Smart Agriculture.

- **Layer-1:** *Agriculture Device Layer* is the base layer of the smart agriculture architecture. It comprises of various things like sensors, laid out through the agricultural land, animal paddocks, green houses, hydroponic systems, tagged livestock, unmanned aerial vehicles, agricultural robots, automated fencing and tractors [15, 16].

  These devices or distributed source nodes sense the physical parameters, collect data round the clock in real-time and send them to the gateway node at next layer through the connectivity layer, which is basically a *Wireless Sensor Network (WSN)*. Fig. 5 shows the data sensed by different sensors/cameras in various fields of smart agriculture. For example, in a rice crop field, underground soil sensors and on-UAV sensors and cameras collect the data and send them to the edge for further processing.

- **Layer-2:** This is the *Edge Computing Layer*. This comprises of a number of edge nodes. The number of nodes depends on the specific smart agricultural system. Data collected at layer-1 are processed, filtered and encrypted here. Previously, the prognostic and solution parts were done in the next layer because of the resource limitations at the edge layer. But with recent advancement of hardware and AI at the edge initiatives, trained machine learning models can perform the prognostics and suggest solutions at this layer. However, if the job is resource expensive or not time sensitive, prognostic and inference can both be done in the next layer. For example, if a cow is outside its supposed territory in a livestock farm or needs milking, the necessary measures are performed at the edge computing layer and the farmer is notified.

  Hardware boards are being used as the edge devices [17]. To mention a few common boards and applications, the *Arduino UNO*, has been used in [18] for a greenhouse monitoring and controlling system, the *Raspberry Pi* for a hydroponic system [19], the *ESP8266* for connecting smart agricultural components for managing ambient factors [20], the *ESP32* for smart irrigation [21], the *Intel Edison* for vertical agricultural warehouses [22], and the *BeagleBone* for monitoring of agrochemical processes [23].

- **Layer-3:** The Cloud Computing Layer is the third or topmost layer of the bottom up architecture of the smart agriculture system. This virtual layer usually resides in data centers and can be accessed from anywhere in the world through the Internet [11]. Massive data, collected by the sensors or cameras in agricultural farms need

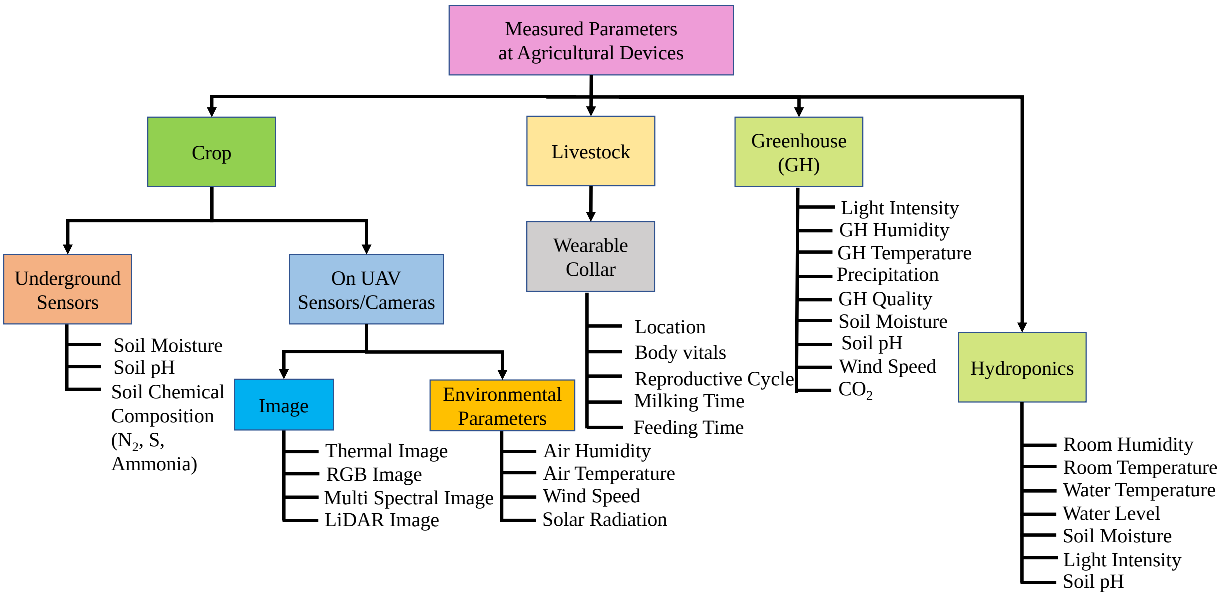


Figure 5: Sensor Parameters in Various Sectors of Smart Agriculture.

to be processed, analyzed and saved. Until recently, most of the analysis and decision taking were done at the cloud along with storing the huge data sets [7, 8, 24]. The high computing power of the cloud allows it to perform various complex tasks in reasonable time. But there are certain limitations of cloud computing which demand new computing paradigms to emerge. Latency, high band width Internet requirements, security and privacy of data are some of the limiting factors which restrain the time sensitive monitoring and managing of smart agriculture.

AI, recent developments in hardware boards and 5G network have orchestrated a new paradigm, the *Edge AI*. It increases the security and privacy of data as it processes data near its point of origin. So data does not travel to the cloud or is shared at the centralized cloud. Edge AI has reduced the latency and dependence on the Internet.

- **Connectivity Layers:** They bridge the various layers. *Connectivity layer-1* gets the physical parameter data from layer-1 and passes them to layer-2. Processed data from layer-2 are passed to layer-3 by *Connectivity layer -2*. Various transmission range communication networks are used in this layer depending on the area to be connected as in Fig. 6. When data is transferred from the agriculture device layer to the edge computing layer, near range ZigBee, Wi-Fi, Z-Wave, Bluetooth, Radio Frequency Identification (RFID), and Near Field Communication (NFC) are commonly used, whereas for longer ranges SigFox, LoRaWan, and Narrowband IoT (NB-IoT) are used [17]. For example, for a smaller farm in a remote village where the network bandwidth is limited low battery consuming Z-Wave is a good choice. But for larger farms, LoRaWan is suitable for its low energy usage and long distance transmission capability. Bluetooth low power has been used for monitoring soil and air along with water management systems in [25], and ZigBee for managing an irrigation system in [26]. RFID is extensively used in the smart agricultural industry [27, 28, 29, 30, 31, 32]. LoRa has been used for water management in [33].

  When the processed data are sent from the edge computing layer to the cloud layer, cellular technologies like Ground Penetrating Radar Services (GPRS), Long-Term Evolution (LTE), 3G/4G, and 5G are used. The recent 5G technology has low latency, high reliability, large coverage areas, high data rate and new frequency bands [9]. This can greatly assist smart agriculture to advance. GPRS has been used for irrigation in [24]. New initiatives have started using 5G [34, 35]. The successor of the 5G network is 6G cellular technology which is under development. It will be much faster than the existing mobile networks. Flexible decentralized models will propel various areas like edge computing, AI, and blockchain which will advance the growth of smart agriculture.

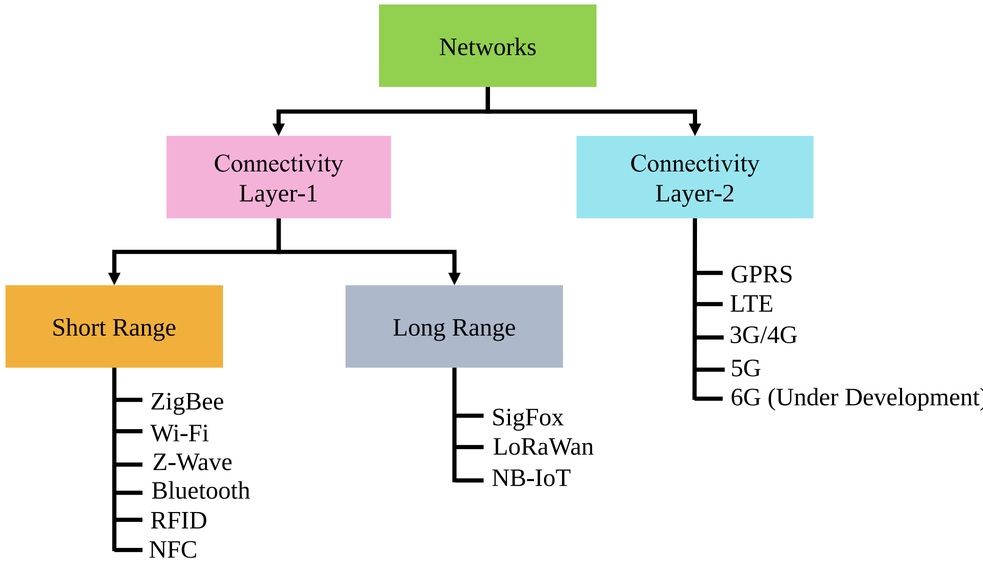


Figure 6: Various Networks for Smart Agriculture.

4 Internet of Agro-Things (IoAT) based Agricultural Cyber-Physical Systems (A-CPS)

The IoT is the network of interrelated physical things, devices, objects with unique id for connecting and sharing data with other devices and systems through the Internet. Implementation of the IoT in physical systems gives birth to Cyber-Physical Systems (CPS). CPS are hybrid systems of physical entities and software or computing capabilities. It is a modern way to define an industry. Smart cities and smart villages include one or more CPS like smart health, smart agriculture, smart energy, smart transportation, smart citizens, renewable energy, etc. A-CPS is the core of smart agriculture. It revolutionizes the agricultural industry. As the Internet of Medical Things (IoMT) forms Healthcare Cyber-Physical Systems (H-CPS), the IoAT forms A-CPS [6].

The IoAT is a data driven system. Constant data collection, processing, and measures are taken to make the workflow highly efficient. Fig. 7(a) shows such an iterative system workflow which allows farmers to take actions readily if any issue is observed. The cycle consists of five stages:

- **Data Collection:** First, various things ("T") or sensors connected through the Internet ("I") collect the data at sensor level or end level.
- **Data Processing:** Second, if any data processing is needed to make the data compatible to the model, it is done in this phase at the edge level. E.g. if the sensor data is not in range or the photos taken by an UAV are needed to be changed to gray scale or any encryption of data is needed before sending to the cloud, they are performed here.
- **Prognostic:** This is mostly done in the clouds for existing technologies. The data, processed at the edge, are analyzed here from the predefined rules or models (mostly ML, Fuzzy Logic (FL), and Arificial Neural Networks (ANN) based). This is where data is stored for future use. The *edge AI* initiative is transforming the scenario.
- **Solution:** Once the issue is detected in the cloud platform, the solution is suggested. This stage can be done in the cloud or at the edge. E.g. if part of the farm land is dry, this stage suggests which valves of the irrigation system need to release what value and how long to optimally water the dry patch.
- **Measures Taken:** This is the final stage of the cycle where the implementation of the solution is performed. This is performed by the IoT device. In the previously mentioned example, the opening of the valve of the irrigation system is performed here.

The cycle continues to serve the whole farming process optimally. Fig. 7(a) shows that when ML based tasks are performed in the cloud and edge settings, the decision or solution is sent to the IoT device for measures taken there. But, TinyML as-a-service is bridging the ML and embedded worlds. Instead of "outsourced" the decision to the IoT device, the ML based task is being performed at the limited resource IoT device only. In this new era, Fig. 7(a) is changing to Fig. 7(b).

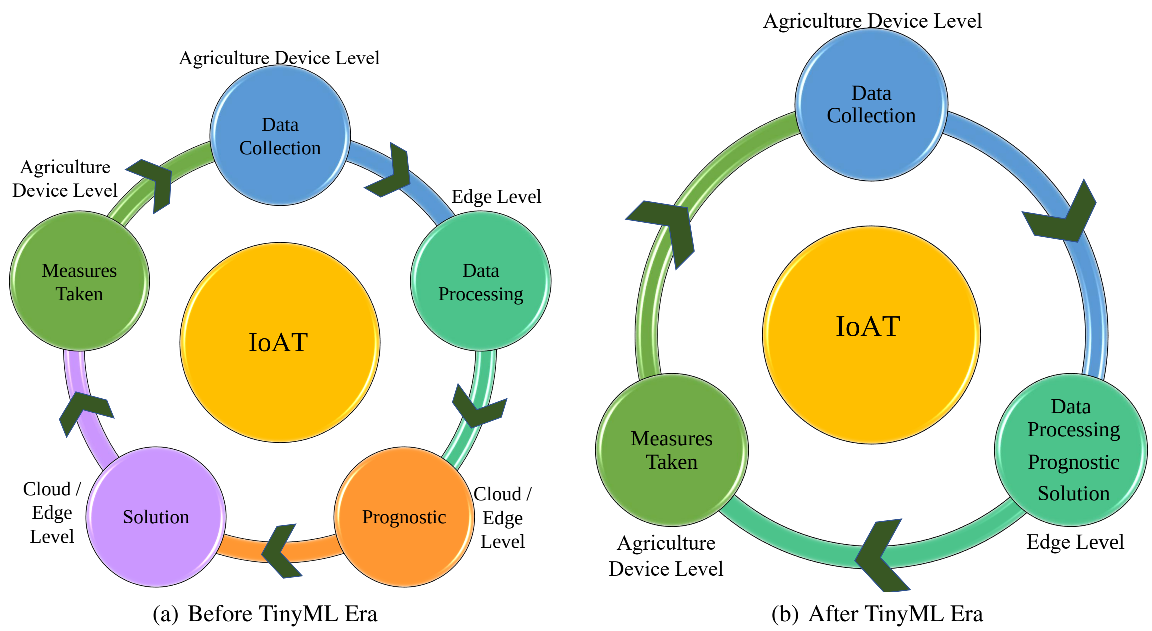


Figure 7: IoT Based Smart Agriculture Cycle.

5 Smart Agriculture: Applications

In this section, application areas of smart agriculture are discussed. Fig. 8 shows some application areas of smart agriculture, e.g., crop management, smart irrigation, livestock monitoring, and pest control and Fig. 10 shows some more applications, e.g., smart greenhouse, UAV and autonomous tractor, and hydroponic system.

5.1 Crop Management

Crop Management is the process of analyzing the economical, ecological and sociological aspects which constitute an important part in the crop selection, cultivation and marketing.

Crop growth, water resources availability, labor, insurance and environmental factors guide cropping patterns. Ecological factors contribute to a change in cropping patterns. For instance, in areas with depleting water resources and groundwater tables, traditional crops like paddy cultivation, which requires abundant water resources, cannot be sustained. The market for an agricultural product, as well as different countries, export and import policies, also affect crop selection. Once a crop has been selected then crop cultivation is the next important aspect.

Using the IoT, farmers are equipped with the latest technology and sensors placed in-field monitor plant growth. For instance, ultrasonic sensors are placed in the field to monitor the presence of pests and insects affecting plant growth. After identifying the presence of pests, high frequency sound waves are generated to remove the pest and the farmer is also notified of the pests' presence for further help [37].

The flowchart illustrating the concept of Smart Farming is detailed in Fig. 9.

5.2 Soil Monitoring

Soil moisture plays an important role in the overall farming process. It is responsible for photosynthesis, respiration , transpiration and transportation of minerals during the plant growth process [38]. Soil monitoring constitutes an important role in farm decision making. Cropping patterns depend on various factors like water availability, soil salinity, pests, moisture, pH and humidity. These factors help in assessing soil health. Sensors on the field monitor soil temperature and humidity and the analyzed data are sent to the cloud. Farmers will receive an alert on a range of factors and cropping patterns are analyzed and decided based on salinity content and soil nutrient level, humidity, and temperature. Soil moisture is a vital aspect in plant growth process as water is an important component in photosynthesis, regulating temperature and acting as a carrier of food and essential nutrients for the plant growth. Humidity controls the nutrient supply and regulates the rate of transpiration for optimum plant growth. The ideal humidity for vegetable

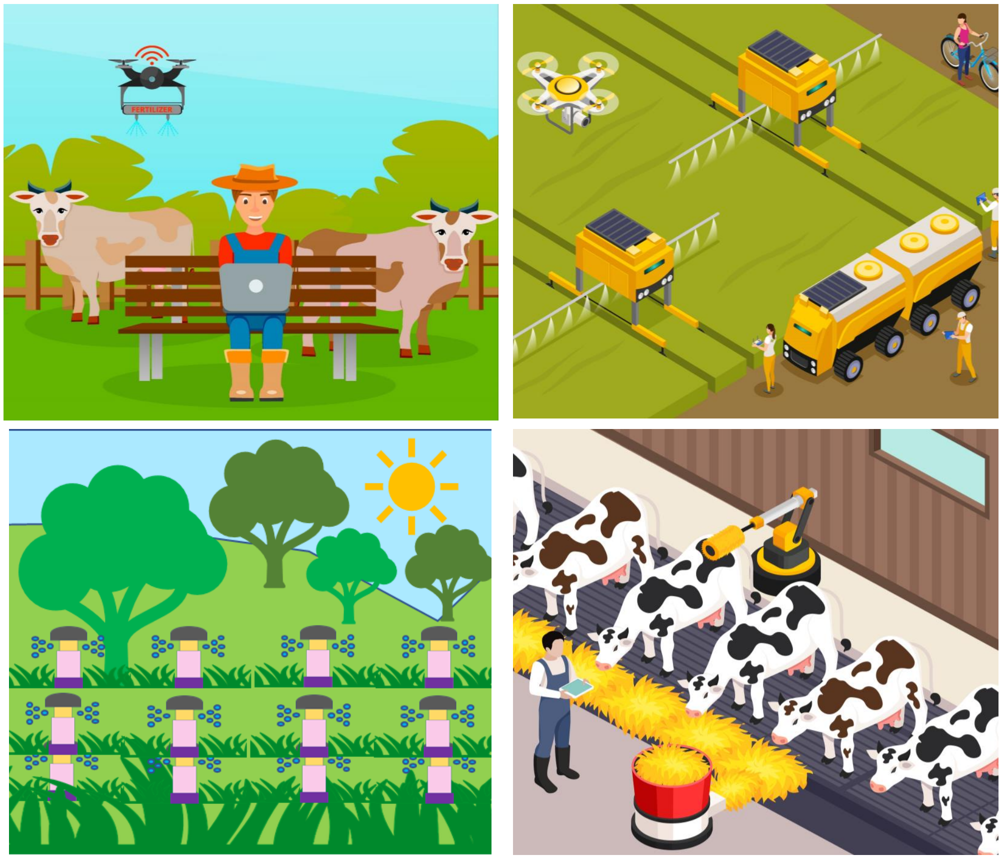


Figure 8: Applications of Smart Agriculture - Crop Management, Pest Control, Smart Irrigation, Livestock Monitoring [36].

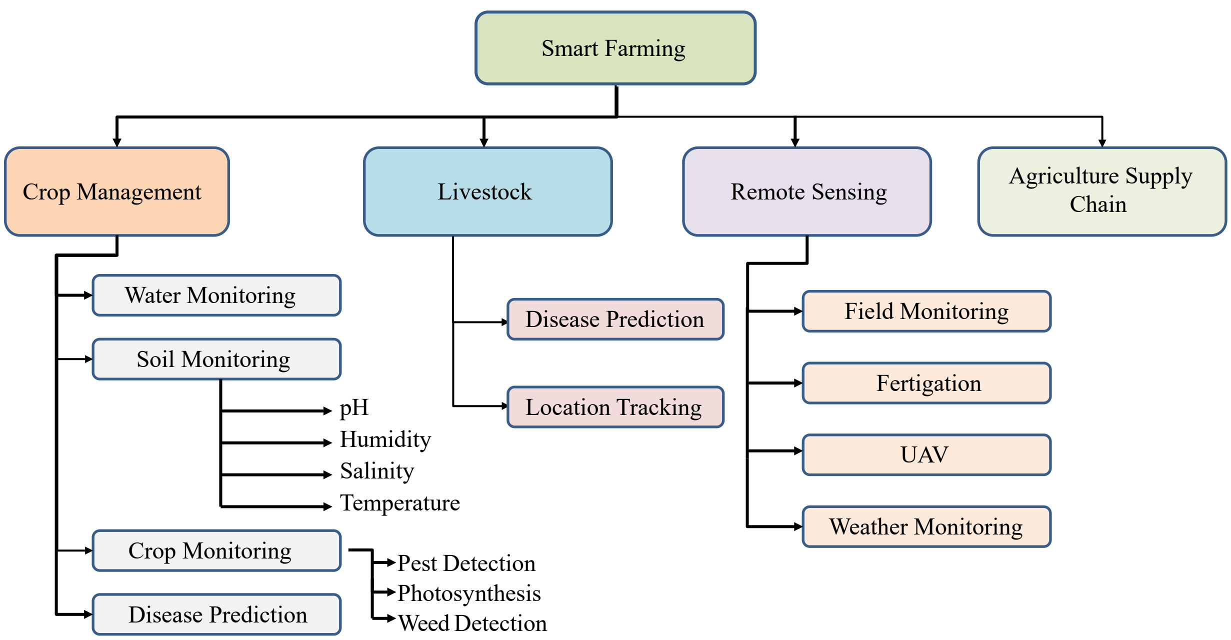


Figure 9: Applications of Smart Agriculture.

plants cultivation is 50% to 60% [39]. Soil moisture sensors placed inside the root of plants analyze soil moisture level values to facilitate optimum utilization of water resources [40, 41].

5.3 Smart Irrigation

Smart irrigation is the process of improving the quality and quantity of yield with optimal utilization of water using the latest technologies. It conserves water by optimally watering the plants. There are two types of irrigation systems - weather based and soil moisture sensor based. Weather based irrigation systems receive temperature and rainfall data from a local mini weather station and a controller regulates the irrigation. In soil moisture sensor based irrigation systems, sensors placed inside the turf of trees, accurately determine soil moisture content. In this type of irrigation, accurate values of humidity and air temperature along with weather monitoring and cropping pattern are required to irrigate the field. Data is sent to the cloud and actuators like sprinklers are activated [42]. The soil moisture sensor values guide the irrigation schedule per unit area of farm. The micro level analysis and scheduling of irrigation and efficient actuation ensures optimum crop growth and 100% efficiency in water utilization [43]. Farmers can operate the irrigation system from a smartphone based mobile application. This irrigation system is based on data from temperature, humidity, soil moisture and ultrasonic sensors placed in the field [44]. The smartphone based mobile application for automatic irrigation is connected to the cloud for analysis using a user friendly mobile application where farmers can perform actuation by enabling the irrigation pumps to water the farm.

5.4 Livestock Monitoring

Livestock management constitutes an important part of smart agriculture. An IoT enabled livestock health monitoring system enables farmers to monitor the health of cattle herds, track grazing animals, and optimize breeding practices. Cattle health can be monitored automatically by measuring body vitals like heart rate, blood pressure or respiratory rate using a wearable collar or RFID tag. This has a two fold advantage - saving man power and providing time sensitive treatment to the animal which in turn stops spreading of diseases. For this purpose, Global Positioning System (GPS) tracking is used [42]. It also can prevent accidents to the animal. RFID tags are also used in animal identification and tracking [45].

5.5 Remote Sensing

Remote sensing in agriculture can help farmers receive real time data on the crop using drones which record high quality images to map the farm fields. They can also be used to check the crop yield using the information on crop health and the condition of farmland. Remote sensing can be used to map soil conditions and enable farmers to decide which type of soil is better for a particular crop. Weed and pests can be detected and proper pest control mechanisms can be adapted. The most important application of remote sensing is weather forecasting and monitoring. It can be used to track rainfall, drought conditions and in identifying water resources, thereby alerting farmers beforehand on availability of water and on weather so that capital and crop planning can be done in advance [46]. Normalized Difference Vegetation Index (NVDI) values, which are one of the most important parameters to quantify the crop cultivation process, are used to notify yield prediction and plant growth [47]. Remote sensing instruments on the farm field are used for monitoring abiotic stress agents with the best possible spatial resolution [48].

5.6 Smart Greenhouse

In the wake of global climate change, and diminishing natural resources the agricultural industry welcomes technology supported farming techniques. Smart greenhouse is one of them. It is an indoor controlled environment tailored for plants. It is a self-isolated farm monitoring ecosystem integrated with IoT, and AI/ML technologies. It protects the farm from wind, storms, and floods. It increases the efficiency of productivity without manual intervention.

Solar powered IoT sensors are placed inside the greenhouse for monitoring the vitals for vegetables, fruits and other horticultural crops. Automatic drip irrigation can be employed using soil moisture sensors placed inside the root of the tree. If a threshold value is reached, the in-field actuator waters the farm accordingly. Use of LED lighting can better cater to the plants' needs. A controlled illumination with specific wavelength and intensity can revamp the plant growth and all year-round yield.

Drip fertigation techniques can be used to sprinkle sufficient amounts of minerals like potassium, phosphorus and other minerals required for optimum growth and good health of plants. Smart greenhouse cultivation is increasing as the technologies are at the farmer's disposal and demand is growing for organic fruits and vegetables using smart green techniques [49]. A decision support based IoT friendly smart greenhouse system has been presented in [50] for increasing productivity of rose plants.

Figure 10: Applications of Smart Agriculture - Smart Greenhouse, Agriculture Robot, UAV and Autonomous Tractor, Hydroponic System [36].

5.7 Unmanned Aerial Vehicle

In the current agricultural industry, the usage of UAV, a.k.a drones, has been steadily increasing. They are being used for crop mapping, field monitoring, remote sensing, fertigation, and weed detection. Drones can be a savior for taking photos in large farming areas, mountainous regions or remote areas. The NVDI is calculated from the drone taken images to asses the crop health. It determines water level, stress condition, plant nutrition, and pest infestation. It can guide the entire crop cultivation process [51, 52, 53].

5.8 Autonomous Tractor

Cutting edge technologies are changing the agriculture industry. The Industrial Internet of Things (IIoT) has propelled from crop management, soil monitoring, smart irrigation to pest control, livestock management or agro marketing. We can expect in the near future farming with autonomous, intelligent, and smart instruments. An autonomous tractor is an important part of these instruments. It is a programmable self-driving vehicle. It can perform tillage, and spraying fertilizers. They are equipped with GPS, lasers and cameras and can function on their own without requiring farmers to monitor them. Autonomous drones are used along with these smart tractors and are used in weed detection, pesticide spraying, field monitoring and surveillance for sustainable agriculture [54]. The autonomous tractors used for spraying and mowing in orchards have perception systems to detect obstacles and remote aided guide for performing agricultural tasks. The perception system uses cameras for geometry based obstacle detection and path identification [55, 56].

5.9 Urban Farming

The increased urbanization rate poses an alarming situation in densely populated cities. A new approach to farming has emerged to offer a sustainable farming solution in those areas. Hence the practice of urban or vertical farming has gained prominence among urban populations. It takes up 3-D space for farming with controlled water, nutrients,

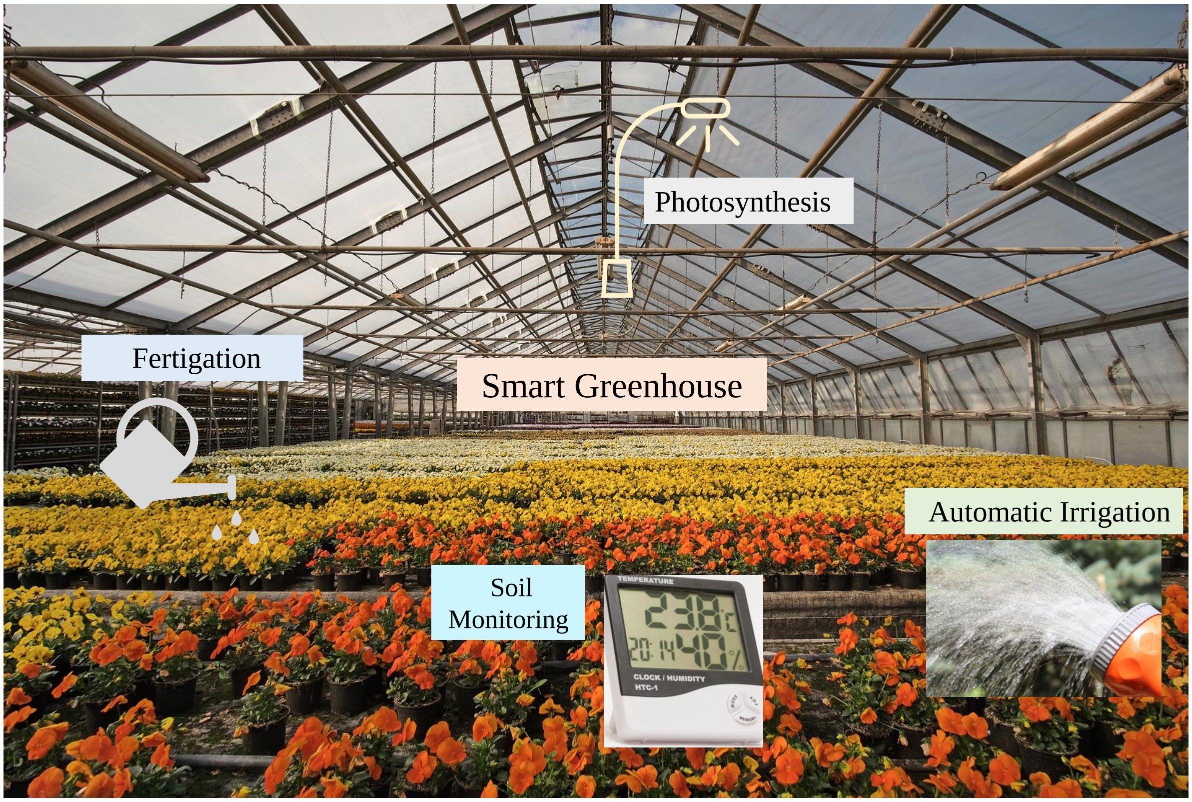


Figure 11: Smart Greenhouse.

minimal pesticides, and artificial lighting sources. The practical limitation of vertical farming system is generation of artificial light sources for plant growth and the large costs involved [57].

- As the name suggests, hydroponics is a water based system where plants get all the nutrients from the nutrient rich water solution [58]. In hydroponic systems, the nutrient supply needs to be continuous. These systems can be operated through mobile apps. In [59] such a mobile app controls an Arduino controller for watering the plants to manage the hydroponic system.
- Aeroponics is a similar system but instead of submerging the roots in the water, the roots are misted. Research shows that aeroponics plants have more nutrients than hydroponics plants [60]. In the International Space Station, this technology is used for growing plants.
- Another recent farming system is aquaponics which is essentially a hydroponic system but the nutrients (phosphorous, nitrogen) are not mixed from the outside. Fish in the same tank generate those nutrients.

5.10 Agriculture Marketing

Proper marketing of the produce is an important aspect of the economic growth of a society. The presence of middle men causes inflation and both consumers and farmers lose. Smart agriculture changes this scenario. Farmers can sell the product directly to the consumers using various agro-marketing apps. Ethereum based blockchain has been used as a platform for trade negotiations between farmers and end consumers [61]. A food supply chain has been implemented with the help of blockchain [62] from updating the distributed ledger at the production phase to the final distribution phase.

6 Smart Agriculture: Challenges

Traditional Agriculture has been modernized and eased by Smart Agriculture processes. But there are still many challenges needed to be addressed for the adoption of technologies to scale. These issues are associated with a variety of aspects which are discussed in the current Section. Fig. 12 shows some of the major challenges of Smart Agriculture.

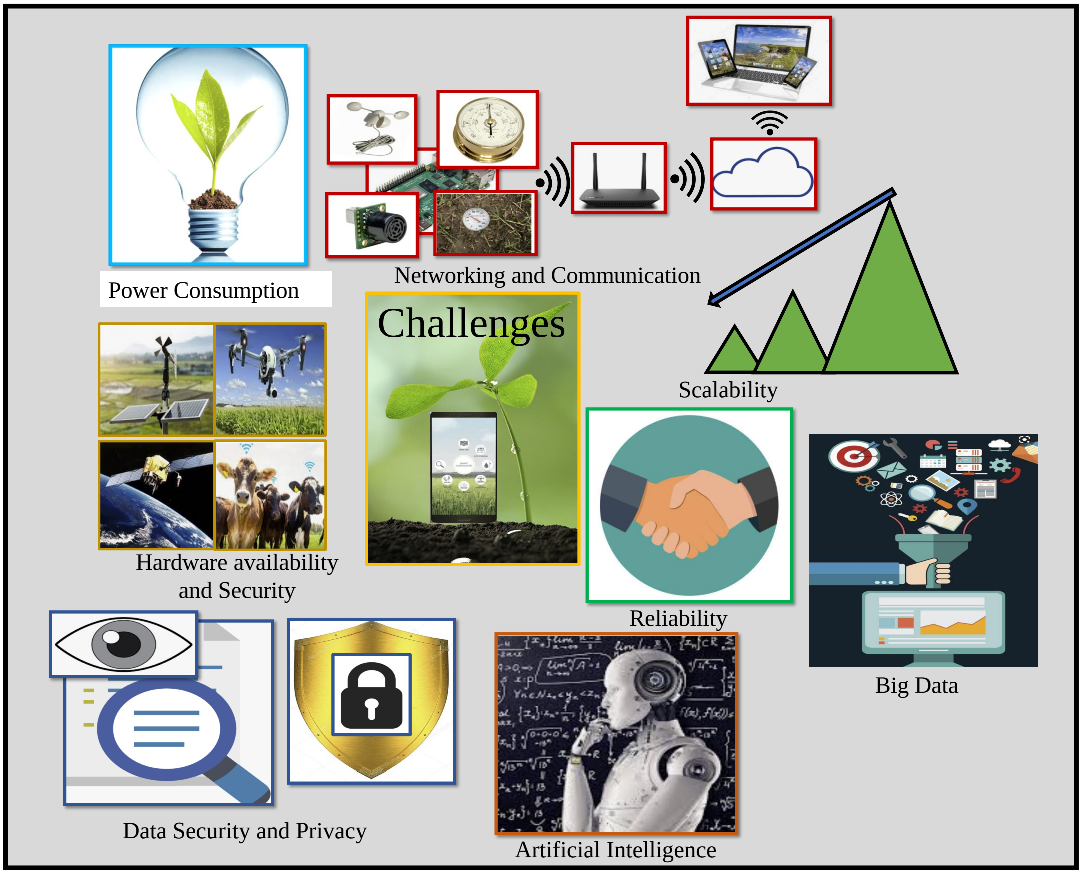


Figure 12: Major Challenges in Smart Agriculture.

6.1 Power Issues

Most smart agriculture activities utilize large machine automation which requires high amounts of power to operate. As farms are generally vast in area and require many electronic components, it is not unusual to have very high power requirements. This has been a bottleneck for wide adoption of such automation processes in large farms. Some of the solutions propose the use of clean energy from renewable sources like solar, wind, and hydro and provide continuous uninterrupted power to the machinery [63]. This has been an area of interest for many researchers and research is ongoing to implement and improve such renewable energy sources for smart farming [64, 65]. Some of the issues with these alternative power options are the storage and transmission of power, along with uneven energy requirements at different location of the farm. An efficient microgrid architecture is required to overcome such issues and research has been done in this area to propose an efficient smart microgrid working along with renewable power sources in [66, 67].

6.2 Power Consumption

For a seamless, reliable and sustainable operation of the smart agriculture farm, as IoAT devices are needed to be operated by alternative power sources, the deployed models are required to be less power hungry. They should be capable of working in a low resource setting.

6.3 Hardware Availability

Smart Agriculture requires different sensors and devices for sensing different environmental and system parameters. After acquiring the data, the devices act upon those signals to give better predictable yield. Availability of specific hardware is a bottleneck in this scenario.

6.4 Hardware Security

By 2020, the number of IoT connected devices are believed to be 50 billion [68]. These IoT devices are needed to be robust and resilient against various attacks. But demand of simple hardware with low price compromises hardware security. Hardware Trojan and Side Channel Attacks are the most common hardware security threats for IoT devices, consequently limiting wide adoption of IoT network in critical applications. Hardware Trojans make use of malicious hardware modifications by the adversary which can be used as a backdoor to control the system and to perform attacks. These are very hard to detect and some methods include performing electronic microscope scanning on de-metalized chips [69] and studying power and delays within the circuit and also inspecting the PUF which acts as signature of these electronic devices [70]. Side Channel Attacks are another common hardware security threat which make use of side channel signals to retrieve confidential information like cryptography keys. Some of these side channel signals include electromagnetic emanation, power profiling and timing analysis [71]. As IoT networks are more prone to these issues, many solutions have been proposed in [72, 73, 74].

6.5 Networking and Communication

Machine-to-Machine (M2M) interaction is one of the most common aspects in smart agriculture. This makes use of different network and communication protocols to share data and work collaboratively towards a common task. Most of the applications make use of many different communication networks like ZigBee, Wi-Fi, LoRA, SigFox, and GPRS. Establishing and maintaining such huge networks is expensive and not a viable option in large, open farms due to physical damages and threats. Research directions have been explored and some solutions for efficient communication networks have been proposed [75, 76, 77]. Additionally, some research has integrated communication equipment with other smart devices making it viable for uninterrupted communication such as Solar Insecticidal Lamps (SIL) and WSN to create a novel agriculture thing, SIL-IoT [78]. The need for more secure and robust communication is very high in smart agriculture applications and requires further research and new affordable technologies.

6.6 Connectivity Issues

In many rural areas across the globe reliable high bandwidth Internet connection is not available, which stalls the existing cloud based computing and prevents the advancement of smart agriculture. Tall trees or hills can also stop the line-of-sight GPS communication [79].

6.7 Data Security and Privacy

To maintain data privacy and security during data transmission, robust cryptography techniques and security measures are needed. However, due to the minimalist design of IoAT sensor nodes and underlying protocols they are not resource intensive. Practicing security measures in a resource limited device is difficult in today's existing technologies. Thus data privacy and security has become a serious challenge in smart agriculture. As most of the processes in smart agriculture are automated, an adversary can manipulate these processes to create chaos in the network. This may lead to very serious consequences for yield and overall quality of farm production.

6.8 Scalability and Reliability

Agricultural farms vary in their size from smaller individual farms to larger commercial farms. They need different quantities of field sensors. These sensors generate a varied amount of data. Hence, any agriculture technology is needed to be scalable. The devices are required to be reliable, so that the number of redundant devices to accommodate fault tolerance can be lower. It will significantly reduce the cost.

6.9 Big Data Challenge

Massive amounts of heterogeneous data is collected by the sensor nodes or cameras in smart agriculture. Traditional ways of processing this enormous amount of data are insufficient and BD analysis comes into play. Big data has the capacity to explore massive datasets. It improves the efficiency of the end-to-end supply chain in smart agricultural systems, mitigates food security issues [80], provides predictive analysis, real time decision, and introduces new business models [81, 82]. Support Vector Machines (SVM) and ANN have been utilized to integrate big data platforms for milk production chain security [83]. Fig. 13 shows the big data workflow in smart agriculture systems based on [80, 82]. It starts with the data collection at various sensor nodes and ends with the various data analysis methods including both traditional and big data analysis.

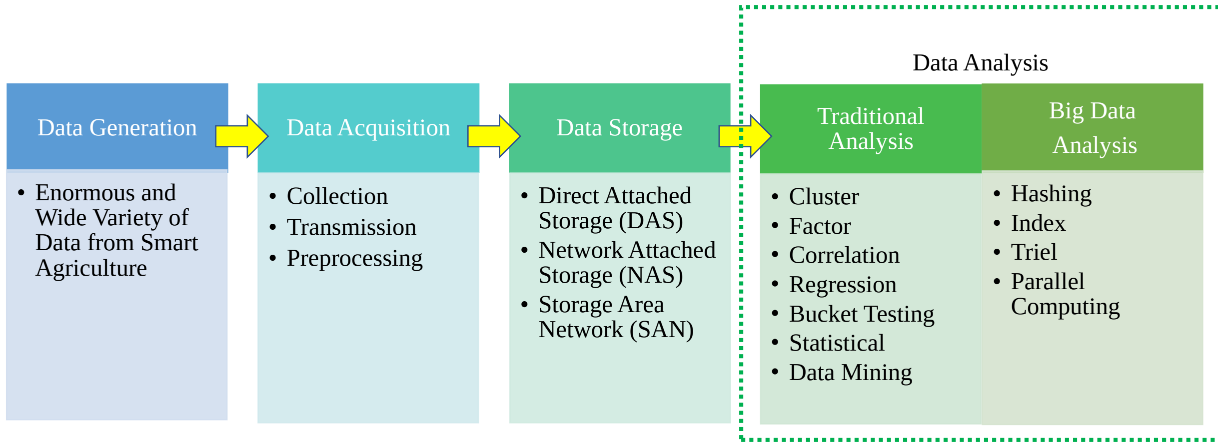


Figure 13: Big Data Work Flow in Context of Smart Agriculture.

6.10 Challenges of AI

Though AI is a logical step toward smart agriculture for sustainable, efficient, and cost effective farming, there are some constraint factors which pose big challenges to applying AI in the agricultural industry:

- There is a lack of connection between the agricultural industry and AI research field. So, the problems faced by farmers are not well known to AI researchers and similarly farmers are not well aware of the existing AI technologies. More interdisciplinary collaboration is needed to solve this two-fold problem.
- As AI applications in agriculture are emerging, there are no well established policies and regulations. Thus, many legal aspects of smart farming are unanswered. Until recently, most of the existing AI-IoT solutions were cloud based and therefore cyber attacks, data security, and privacy concerns kept farmers away from embracing AI techniques. To mitigate this issue, a new IoT setting "Edge AI" has emerged. Edge AI processes sensor data at the local level, and it provides higher security and privacy in data along with lower latency and cost.
- Another challenge for AI in agriculture is lack of data. AI is a data-driven technology. The unavailability of proper data is a barrier to applying various AI techniques.
- In remote rural areas where higher bandwidth mobile networks are not available but agriculture is the main industry, Edge AI can be a game changer there. It expands the possibilities of smart agriculture. Convolutional Neural Networks (CNN) have been used in [84] at the edge layer to compress the sensor image data and then the compressed data has been sent to the fog layer using Low-Power Wide Area Network (LPWAN) technology.

6.11 Technical Malfunction

Technical malfunction, e.g., sensor damage can disrupt the technology. A huge amount of loss from wrong decision-making of devices can introduce multi domain damage. For a paddy field, if the sensors are damaged by hail, they will not predict the water content of the soil correctly which in turn can damage crops, impact food supply chain, and cause rice price imbalance.

6.12 Lack of Initial Capital Investment

In rural areas of developing countries where farmers work with a very meager profit margin, initial investment for advanced technologies is not always available. It can decelerate the mass scale use of smart technologies.

6.13 Unavailability of Uniform Standards

Different countries use different standards of units and technologies which demand customized solution. This increases the price. A uniform standard across the world will solve the problem [79].

7 Technologies for Smart Agriculture

2021 has been marked as the start of the *Industry* 5.0 era. It arrived at the right moment when various industry sectors are welcoming digital, smart, green and sustainable ecosystems to cope with COVID-19 challenges. It redefines the relationship between "man" and "machine" [85]. In agriculture, the *Industry* 5.0 era will accelerate the arrival of *Agriculture* 5.0. Mainly AI/ML and DLT will orchestrate the advancement along with FL, UAV, agricultural robotics, and alternative farming, as shown in Fig. 14. In this section the two main technologies are discussed.

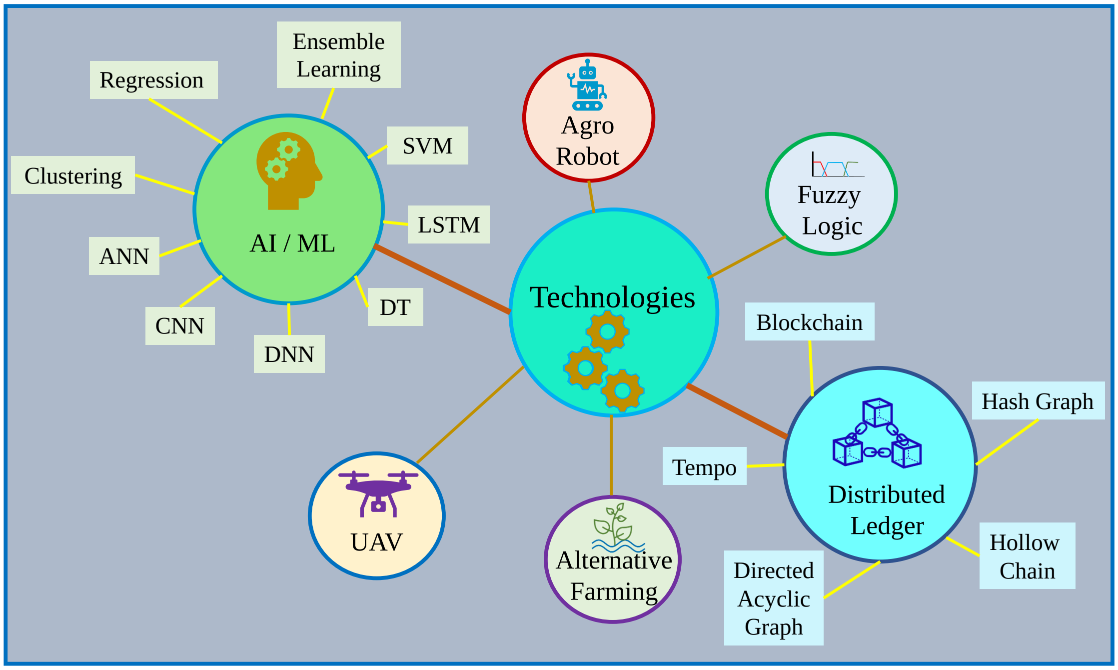


Figure 14: Technologies in Smart Agriculture.

7.1 Artificial Intelligence and Machine Learning

Artificial intelligence is the intelligence displayed by machines that resembles human intelligence. Advancements in AI and ML have shown a lot of promise in various domains such as e-commerce and marketing [86], human resources [87], computer vision [88], multimedia forensics [89, 90], healthcare [91], social media [92, 93], gaming [94, 95], automobiles, and agriculture. In agriculture, AI is used in increasing efficiency, crop yield and profitability, monitoring crop health, monitoring and forecasting climate, optimizing supply chain, managing irrigation systems, pesticide and fertilizer management, weed control, smart sensing and mapping, livestock tracking and geofencing. Researchers are applying Fuzzy logic, various AI/ML techniques including classification, and logistic regression as well as Neuro-Fuzzy logic to agricultural predictive analytics, decision making systems, agricultural robotics and mobile expert systems [96]. Fig. 15 shows the AI tools presented in various literature works on smart agriculture.

7.1.1 Crop Management

Crop management consists of crop production or yield prediction, estimation, and crop supply chain management. Various ML tools have been used in different sectors of crop management. To count the number of coffee fruits on a coffee plant branch [98] and identify the green immature citrus fruits [99], SVM have been used. SVM have also been used for rice crop yield prediction [100]. The branches with full of cherries have been estimated with Gaussian Naive Bayes [101]. ANN have been used to evaluate grassland biomass [102] and wheat yield prediction [103]. Corn and soybean yield prediction has been done in [104] using ANN with better accuracy than regression models. ANN with back propagation have also been used to predict yields from soil parameters [105]. ANN have also been used to predict corn yield [106], rice yield in a mountainous region [107], cotton yield [108], wheat yield [109], maize crop yield [110], tea yield [111], and general crop yield [112]. ANN have also been used in detecting nutrition disorder for crops [113] and predicting the reaction of crops over soil salinity and water content [114]. From UAV imagery, tomatoes have been detected using clustering [115]. Crop growth has been monitored in [116].

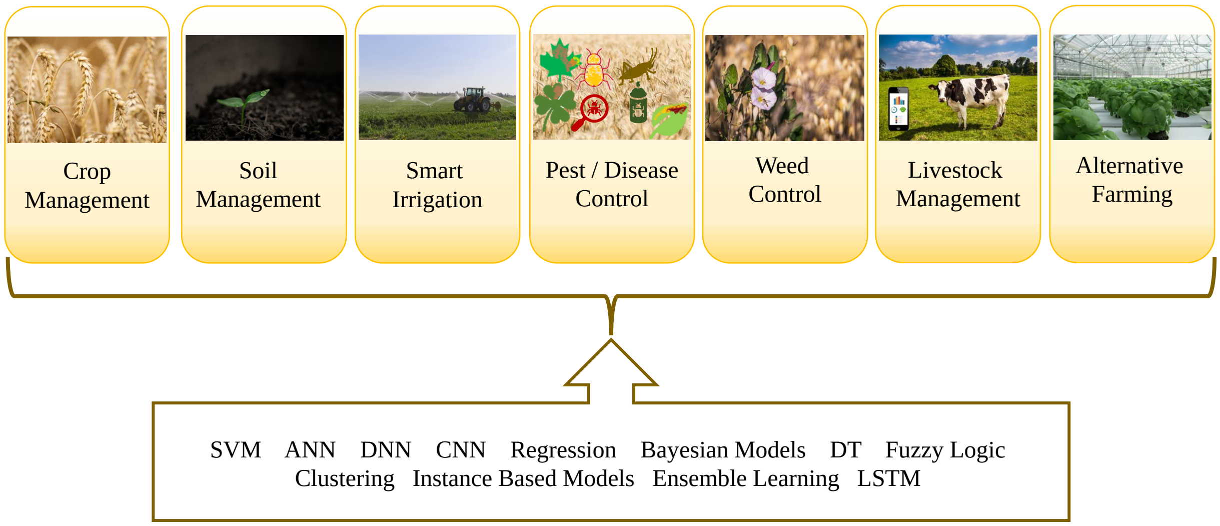


Figure 15: AI Tools for Smart Agriculture [97].

7.1.2 Soil Management

Soil property management such as soil moisture, temperature, and nutrient content is an important part of smart agricultural systems. Its benefits are two fold - increasing crop yield and preserving soil resources [117]. But the process is time consuming and costly. So, various inexpensive and autonomous ML techniques are being proposed to have a reliable soil management system [97]. Mostly, the data from sensors, satellite images or images taken by UAV are used as the input of the ML models. ANN, SVM, and autoencoders have been used in predictive analysis. ANN and Multi-Layer Perceptrons (MLP) have been used for suitability of soil evaluation [118]. Phosphorous in soil has been predicted using various ML models [119]. Deep Neural Networks (DNN) have been utilized to extract geo-parcels from high resolution images and MLP have been employed to predict the phosphorous content. Radial basis function neural network have been applied to predict the water retention capacity of soil in Brazilian coastal areas [120]. Soil moisture is also predicted with Boosted Regression Trees (BRT) from UAV-taken images [121] and with ANN in [122]. Health and condition of soil moisture sensors have been predicted using SVM along with the stage of the degradation by using Naive Bayes classification [123]. Autoencoder and SVM have been used to predict the soil salinity from satellite images [124].

7.1.3 Smart Irrigation

Water management is an integral part of smart agricultural systems. Rainfall patterns are changing worldwide due to climate change. Evapotranspiration plays a vital role to assess water resources. Various AI methods have been utilized in smart water management. Deep reinforcement learning has been used for smart water management in a crop field [125]. A multiple linear regression algorithm has been applied to calculate the water needed for greenhouse organic crops and then water valves have been operated automatically with a LoRa Point-to-Point (P2P) network [126]. An ANN system has been proposed in [127] to predict evapotranspiration by carrying out a study in Dehradun, India. ANN and the Penman-Monteith equation have been utilized to predict daily evapotranspiration [128]. A smart irrigation system has been proposed using Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) based models in an Edge-Fog-Cloud setting [129]. Spatial water distribution has been predicted with ANN in [130] for a neuro-drip irrigation system.

7.1.4 Pest/Disease Control

To have optimal yield from a crop field, disease, pest, and weed control are necessary. An automated efficient system can save time and cost. From that perspective, AI techniques are being proposed in various publications. The advancement started with a rule based system [131, 132, 133, 134, 135] in the last decade and evolved through FL systems [136, 137, 138, 139]. Various ANN have been used for different diseases in different crops [140, 141, 142, 143] or for pest detection, e.g., a channel–spatial attention module, integrated with a backbone CNN and a Region Proposal Network (RPN) have been used to detect various pests in a crop field [144] and apple leaf disease is detected in [145] using the GoogleNet Inception network and Rainbow concatenation. An incremental back propagation network has been used with Correlation-based Feature Selection (CFS) to detect pests in a tea plant. The CNN based object detection model YOLOv3 has been utilized to localize the pest Tessaratoma Papillosa and by analyzing the environmental information by LSTM, pest occurrence is predicted with 90% accuracy [146]. YOLOv3 and YOLOv3-Dense models have also been employed to detect anthrax on apple surface in an apple orchard [147]. Single Seed Descent (SSD) has been applied with 84% accuracy in detecting pests and with 86% accuracy in classifying pests [148]. Pest detection and recognition have been performed through k-means clustering and correspondence filter [149]. CNN based models have been used in [150] and in [151] in crop disease detection.

7.1.5 Weed Control

Weed affects yield negatively. So, weed control is another important area in smart agriculture. Weeds are sometimes hard to distinguish from crops. The application of AI in weed control started in the early 2000s. ANN have been employed with Hebbian synaptic modification for distinguishing weeds from crops [152] and the accuracy achieved was reasonable based on the available hardware at that time. YOLOv3 has been used for low cost precision weed management in [153]. Counter Propagation (CP)-ANN with multi-spectral images [154] and a combination of auto encoder and SVM along with hyper spectral images [155] have been utilized to detect weeds. SVM has been used in [156] to detect weeds in grassland cropping.

7.1.6 Livestock Management

AI/ML techniques have been used in livestock management in two ways: animal welfare and livestock production [97]. Animal welfare, or the well-being of the animals has been addressed in [157] for cattle using bagging ensemble learning, for calf using decision tree and C4.5 algorithm [158], and for pigs using Gaussian Mixture Models [159]. AI helps to optimize the efficiency of livestock production. ANN with back propagation has been used in [160] to predict cattle rumen fermentation patterns from milk fatty acids. Pigs' faces have been detected with CNN with 97% accuracy in [161]. SVM have been used for problem detection and warnings in egg production for commercial hen production [162], to estimate cattle weight trajectories for evolution [163], and to predict skeleton weight of the beef cattle [164]. ANN with Bayesian Regularization has been used to predict quality milk production and to reduce the heat stress levels of the cows in a robotic cow farm [165]. A fully connected neural network has been used to predict cow diseases in [166].

7.1.7 Alternative Farming

Alternative farming consists of greenhouse farming, and hydroponics. ML and deep learning techniques are used in those systems for better and precise control with less manpower. Greenhouse air temperature is forecast using fully connected ANN and Root Mean Square Error (RMSE) [167]. ANN have been used for greenhouse tomato yield and growth [168], greenhouse basil yield [169], greenhouse gas emission and energy consumption of wheat yield [170] and that of watermelon [171]. An Recurrent Neural Network (RNN) with back propagation has been used to predict the humidity and the temperature of a greenhouse, powered by solar energy [172] and RNN-LSTM in [173] for climate (humidity, temperature and CO_2) prediction. ANN and Bayesian Networks have been used in hydroponic systems to predict the needed action [19].

Various AI technologies are proposed depending on the location of the computation. For *edge AI* settings, where the AI model runs on the limited resource embedded system itself, research is ongoing to design deep neural network models which have higher accuracy but fewer parameters to train [174]. MobileNet [175], SqueezeNet [176], EfficientNet [177] are such networks where depth wise convolution, down-sampling of data and uniform scaling down of the model are performed respectively. Quantization [178, 179, 180, 181] and pruning [182, 183, 184, 185, 186, 187, 188] are used to reduce the DNN size. Proper choice of hardware is equally important as the algorithms.

7.2 Blockchain and Distributed Ledger Technology

7.2.1 Blockchain as a Digital Technology

Blockchain is one of the recent technologies with promising applications in different fields which include peer-to-peer financial systems [189][190], Real-time Secure IoT systems [191], Smart Governance applications [192, 193], Digital Asset Copyright technologies [194, 195], Smart Healthcare [196, 197], Smart Agriculture and many other industries. The blockchain can be simplistically defined as a peer-to-peer distributed ledger which processes incoming transaction data and updates the shared ledger chronologically based on a set of rules known as Consensus mechanism that are accepted by peers across the network. The main idea behind creating such peer-to-peer networks is to create a reliable and verifiable communication and data storage between un-trusted entities which need to share data and work collectively as a single system. The most commonly used decentralized application structure in the past few decades is the client-server model where instead of housing data on a single central entity it is replicated and partitioned onto multiple servers easily accessed by clients from multiple locations. Even though this model has successfully addressed centralized system problems, it is still prone to security and privacy attacks which can be efficiently addressed using distributed networks. Fig. 16 shows different network configurations.

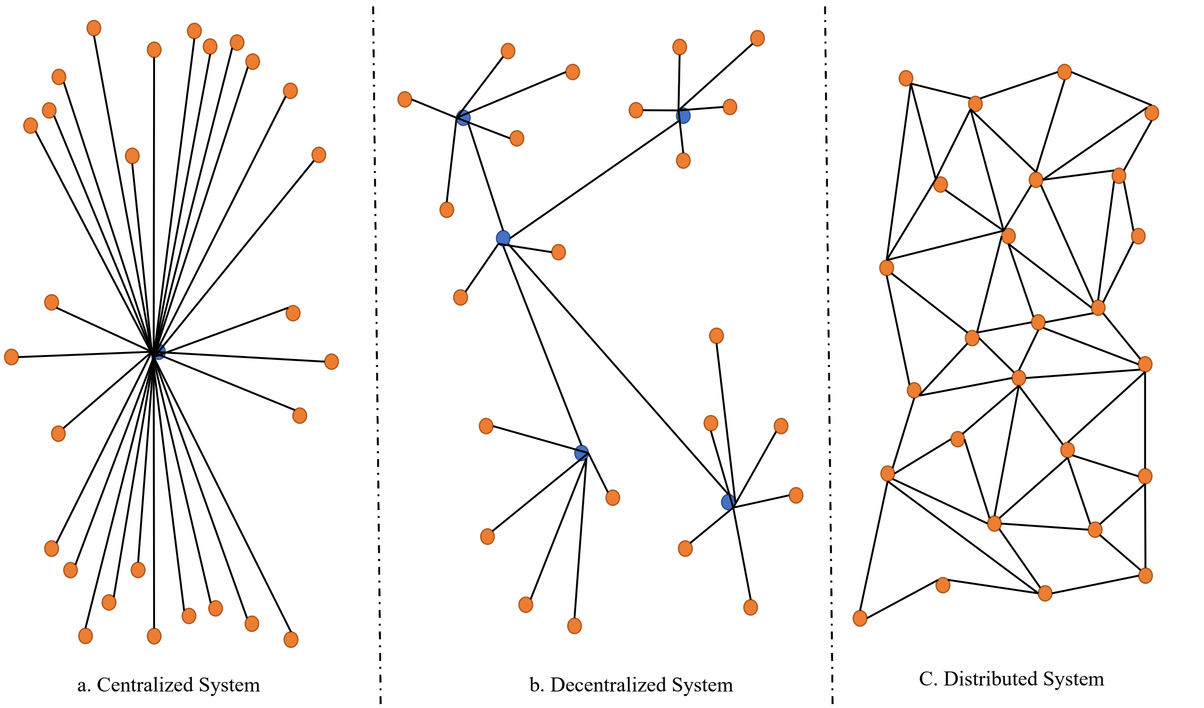


Figure 16: Types Of Networks (a) Centralized network which has single point of information sharing represented by blue sphere and multiple clients represented by orange spheres (b) Decentralized network which has multiple replicated central nodes represented by blue spheres and multiple clients represented by orange spheres (c) Distributed network where there is no central entity

Centralized systems have all the network data housed at a single location which is controlled and maintained by a network owner. The main drawbacks of this system are Single Point-of-Failure (SPoF) and latency in data accessing from long distances. These drawbacks can be avoided by introducing a decentralized system where the data is replicated among multiple central servers which serve different locations effectively even when there is a failure at one of the central nodes. Even though this solved most of the problems, data is still controlled by a third party owner who is responsible for maintaining and storing the client information and interacting with them which may lead to several security and privacy issues. Another disadvantage with such an architecture is lack of data ownership and control on data from clients while interacting with such decentralized systems. Distributed networks can solve these issues by removing the need for central authorities to monitor and verify the network traffic. The IoT has sensor and edge devices which form a distributed network. The data sharing and collective working of such devices can be improved by blockchain technology. Main components of the blockchain include Shared Ledger, Node, Transaction and consensus mechanism.

The blockchain shared ledger is a chronologically connected sequence of blocks of approved transactions. Each block consists of transactions along with the metadata which can be used to verify the integrity and authenticity of the transaction information within. Every node participating in the network will have its own copy of the ledger which will be updated periodically and helps to act as a single point of truth for the network. The ledger is replicated across the nodes in the network to avoid double spending of digital assets. Nodes are the participants of the network which are capable of performing transactions and also participate in network operations. Based on the roles they perform nodes can be peer nodes, full nodes and miners. Peer nodes are less computationally capable and are mainly responsible for generating transactions which utilize the blockchain network to process and handle transactions. Full nodes are nodes with large storage and are responsible for storing the entire trail of transactions. There is no incentive associated with full nodes but these nodes maintain the complete ledger to verify the transactions coming in. Miner nodes are responsible for performing the consensus mechanism where blocks generated are processed based on the pre-defined set of rules called consensus mechanism. These nodes are computationally capable and incentives are given for each block generated by the node. Most popular consensus mechanisms used are Proof-of-Work (PoW) and Proof-of-Stake (PoS), among which PoW makes use of computationally hard cryptography puzzles to select the miner whereas PoS makes use of staking and age of staking into consideration while selecting a miner to generate new blocks. Fig. 17 shows the transactions steps and digital asset verification process in detail.

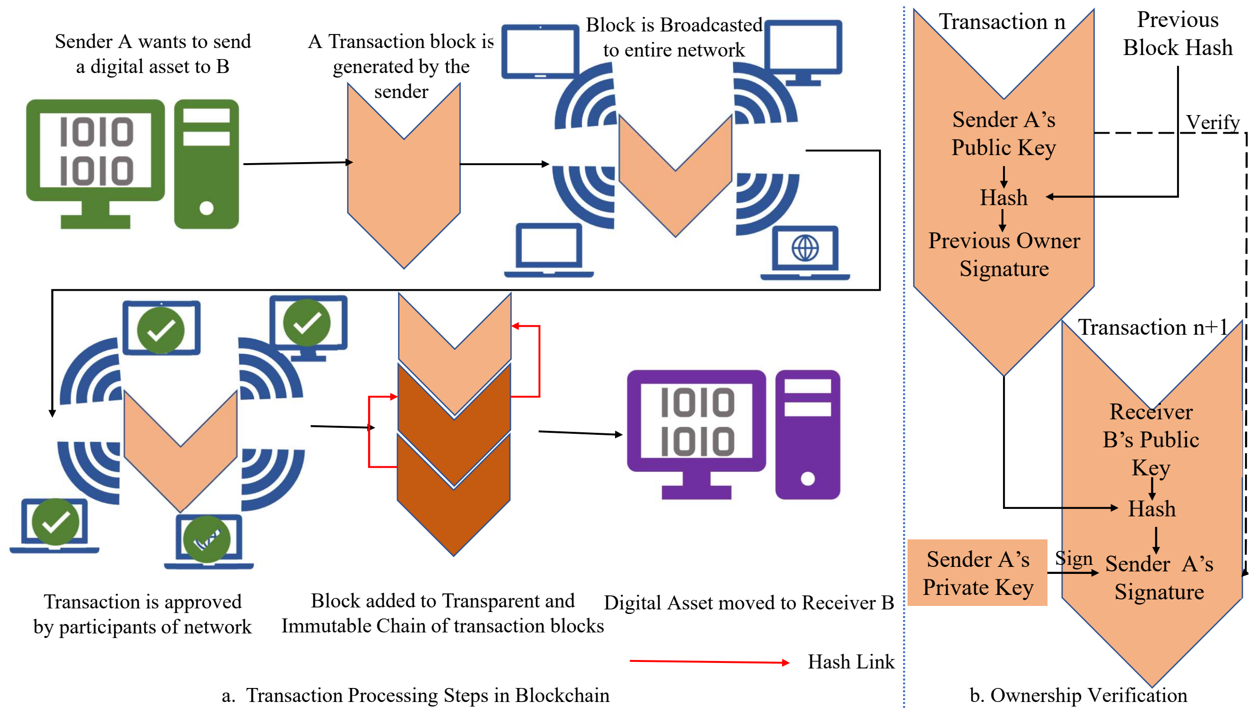


Figure 17: Blockchain Transaction Steps and Digital Asset Ownership Verification.

7.2.2 Relevance of Blockchain Technology in Smart Agriculture

The agriculture sector has evolved by adapting various new technologies to modify farming practices for efficient and better yield of crops [5]. One such enabling technology is the IoT which provides solutions for automating many anthropocentric tasks in farming. In the layered architecture used in the IoT environment in agriculture, *layer-2* or the edge computing layer consists of many Edge Data Centers (EDC)) which form distributed networks with a critical need to communicate and share data between each other to work collectively [198], as in Fig. 18. In order to make these Machine-to-Machine communications more secure, there is a need for central authorities to monitor the data and deploy some cryptography techniques to maintain data integrity and privacy. This can be a challenging task with the number of computing edge devices that are needed while monitoring and controlling a large farm. Furthermore, using such central monitoring system can lead to centralization and other problems like single point of failure and latency issues. These issues can adversely affect farms as automated systems will not behave as expected and result in the reduction in yield or quality of crop.

7.2.3 Blockchain Applications in Agriculture

The blockchain has a large set of applications in smart agriculture and deals with different aspects of farm activities. Some of the major applications and related solutions are discussed below.

7.2.3.1 Secure Real-time Data Sharing

Data security and privacy is one important aspect in smart agriculture which needs to be addressed for efficient functioning of autonomous processes. The blockchain makes use of cryptography techniques and processes transactions in chronological order to maintain integrity of data and avoid adversary attacks such as Denial-of-Service (DoS) and

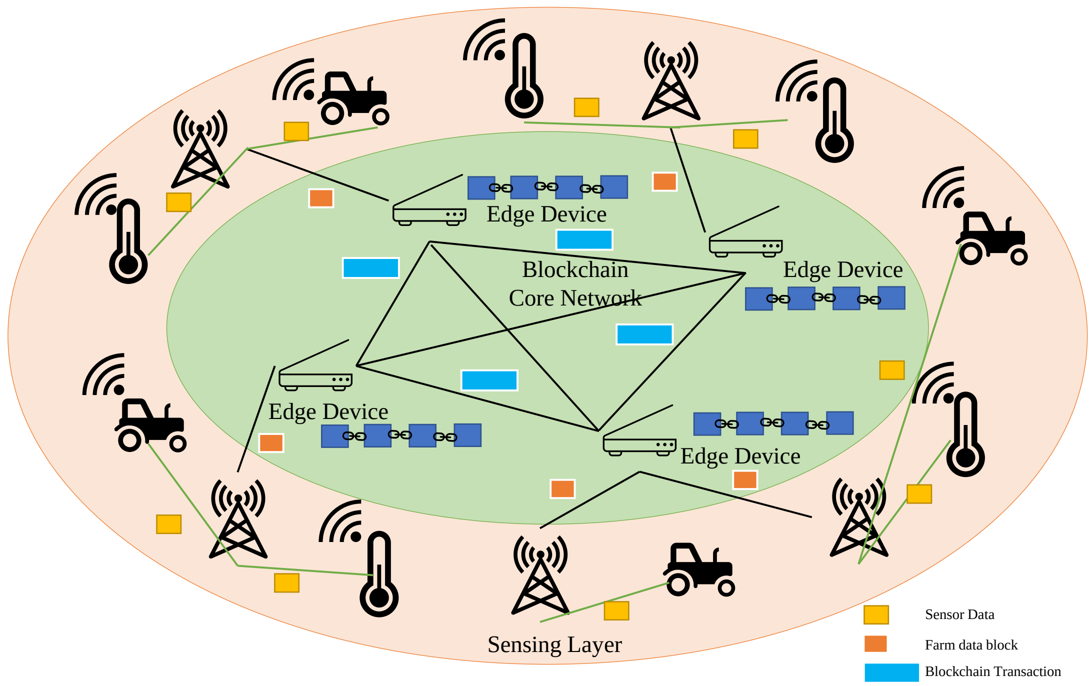


Figure 18: Analogy Between Smart Agriculture IoT Network and Blockchain.

False Data Injection. Apart from data privacy, data ownership and monetization are also problems. Unlike in centralized applications where the data is monetized by a central authority, blockchain based applications can help farmers control the data access at granular levels and can help in monetizing the data on their own. A typical IoT architecture consists of a cloud layer where data from the edge layer is stored and processed to perform automated tasks. One of the main drawbacks with such networks is that the latency and access times vary based on network availability and number of access requests going to the server at a given time. As real-time operation is critical in making decisions, the blockchain can help in developing an efficient real-time data sharing model. Some of the secure models using blockchain for secure data sharing are proposed in [199, 200, 201, 202]. [199] established an identity managed authentication mechanism which makes use of private blockchain and provides a secure information sharing mechanism eliminating Distributed Denial-of-Service (DDoS) attacks. [200] has proposed a system which is a combination of Software-Defined Networking (SDN) technology along with blockchain to detect and prevent attacks in the IoT environment with only minimal overhead. This can be an optimal solution in resource constrained environments like IoAT. [201] makes use of homomorphic computation on encrypted data and follows a similar approach to Practical Byzantine Fault Tolerance (PBFT) and is based on the threshold number of correct responses from the server relevant smart contracts will be run. For the implementation, the Ethereum blockchain was used and the response times were computed to be 22 sec as the block generation time of Ethereum is fixed at 15 sec and can be further improved by adapting second generation blockchains with shorter block times. [202] has proposed a novel key management architecture which can address issues of centralized systems using blockchain while increasing scalability and reliability. [203] made use of distributed ledgers instead of traditional blockchains which are resource intensive to increase the scalability and real-time data availability in Smart Agriculture systems.

7.2.3.2 Community Farming and Local Markets

Community farming needs collective intelligence and transparent sharing of weather, crop disease or product demand data to help crop choice and achieve better yield. Along with this, local markets will enable the farmers to monetize their product more efficiently with greater profits. The blockchain can help in organizing and managing such applications for farmers to enable them to both produce and realize better profitability. Some of the works towards this area have been presented in [204] which made use of the Ethereum platform to remove the intermediaries to establish an ethical supply chain and provide deserved profits to farmers. Fig. 19 shows the logistics present in the Supply Chain Traceability.

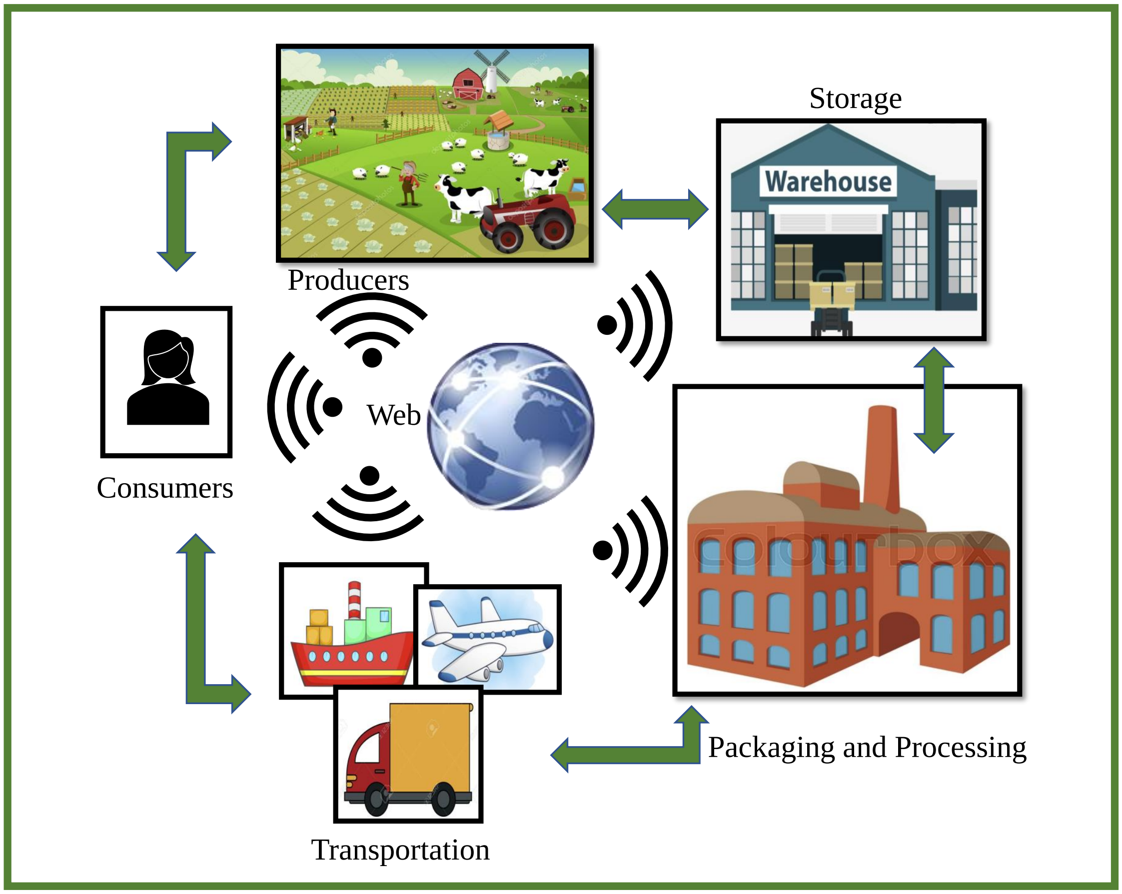


Figure 19: Supply Chain Traceability in Smart Agriculture.

7.2.3.3 Supply-Chain Traceability

Globalization is the trend which enabled product availability at even remote places. This has made global food supply chains more complex by involving multiple entities working together throughout the process. One of the major problems with such complex food supply chains is traceability and consumer confidence. It is very common to see food-borne disease outbreaks. In such scenarios, the most common approach is to dispose of the entire inventory as testing each product for infestation is not possible. Instead, tracing the product back to the farm from where it was produced can help in determining which products are affected and reduce food wastage. As an end user, a clear and transparent supply chain can help building customer confidence in the authenticity of food. The blockchain can help in this aspect by building transparent supply chains where traceability and authenticity of the food can be easily verified. Many research works have been proposed. [205, 206] makes use of HyperLedger Fabric blockchain to perform a case study on the blockchain based supply chain and discusses limitations. A solution based on RFID technology integrated with blockchain is proposed in [207]. [208] proposed a smart contract based financial solution in supply chains to help in solving the issue of SPoF in traditional Enterprise Resource Planning (ERP) systems. [209] has proposed Ethereum based decentralized applications for tracing the supply chain in organic foods to build trust and confidence from the consumer towards suppliers. [210] proposed an efficient supply chain tracking system integrating blockchain with Electronic Product Code Information Services (EPCIS) and making use of Ethereum smart Contracts.

7.2.3.4 Farm Insurance

Farms are more prone to weather changes and the damages due to weather conditions will lead to financial instability for farmers. Agriculture insurance is based on a farmer paying a fixed amount of premiums before the cropping cycle begins and receiving a payout based on the damage caused by the weather conditions. The problem arises when there is no index available to calculate the amount of damage, hence weather data is used and analyzed by the insurance provider to evaluate an index which forms the baseline for farmers and makes it easy to process these farm insurances. The most common setup is for the insurance provider to make use of weather station data recorded remotely and presented to farmers. Blockchain can help in assessing and accepting premium payments from the farmer using automated smart contracts. Together with that, weather index data can also be made available to farmers with greater reliability. [211] proposes a blockchain based solution for avoiding fraud in insurance. [212] made use of the NEO platform to build a system for drought based insurance. [213] proposed an Ethereum blockchain and hyperledger private blockchain based solution for insurance services using smart contracts.

7.2.4 Limitations of Blockchain

Even though the blockchain has many potential applications in smart agriculture to enhance data security and integrity, there are still challenges which need to be addressed before wide adoption of this technology into the agriculture space. IoT technology used in smart agriculture is resource constrained both in terms of power and computations whereas the consensus mechanism and cryptography components of the blockchain require large amounts of power and computation. The blockchain as such cannot be an efficient solution, hence research is being done to propose various efficient consensus mechanisms which can be implemented in resource constrained environments as in smart agriculture. [214] has proposed a consensus mechanism based on cryptographic authentication and Media Access Control (MAC) address verification which has reduced the computational requirements of the consensus mechanism and has increased the transaction times significantly. Data is another significant problem which needs to be addressed for wide adoption. As the size of each block in the blockchain is predefined and limited, large amounts of data like images are not viable to be stored on-chain. Hence, many researchers are working on making the data stored off-chain while the transaction and access information along with the data are stored on-chain for secure access and integrity. [215] proposed a system which makes use of the Interplanetary File System (IPFS) along with Ethereum smart contracts to share COVID-19 related patient data which can help in enforcing social distancing practices. This can be adopted into smart agriculture for storage of large chunks of data. Multi level access management is also a vital aspect which needs to be addressed. [216] proposed a blockchain system which can operate at multiple levels with different access policies for an efficient and controlled data management process which can be adopted to smart agriculture environments.

8 Datasets for Smart Agriculture Research

Smart agriculture makes use of intelligent devices to collect data to analyze crop yields, livestock management, and economics related to supply. The stored data can help further research into the availability of resources in farming for next generations. Table 1 shows different datasets of multiple formats that we have studied and collected for the current survey paper.

8.1 Crop Yield and Production

Sensors are used to collect data relating to acreage, crop condition, and yield. The amount of crop yield can be calculated by dividing the amount of produce over the harvested area. Crop production can be measured in terms of tonnes per hectare. The U.S. Department of Agriculture (USDA) produces annual reports that include data for yield, acreage, and production for crops, plants, livestock, and animals, along with a Census of Agriculture. Fig.20 shows the graphs for some of the crops, livestock, and expenditures of agriculture in the United States for different years. Additionally, the prices for farming, labor, production, and land values are collected monthly and annually [217].

8.2 Crop Condition and Soil Moisture

Knowledge of soil moisture is a critical factor for the yield and production of crops. In order to execute different agricultural operations easily, data regarding the soil is essential for farmer decision making. Crop Condition and Soil Moisture Analytics (Crop-CASMA) is a web-based geospatial application used to measure soil moisture and vegetation conditions. The data collected is in the form of Geographic Information System mapping format (.gis) [218]. Fig. 21(a) and 21(b) show crop condition and soil moisture analytics in the United States at two different dates.

8.3 Plant Diseases

When a plant gets infected with disease, its vital functions are modified and damaged, leading to harmful consumption for individuals. Each plant species has its unique syndrome. Kaggle is a good source of various datasets regarding different plant diseases. Fig. 22 shows some of the sample images from the Plant Disease dataset [219]. Collecting and

Table 1: Datasets for Smart Agricuture.

Dataset	Source	Dataset Format	Link
Crop Yield & Production	USDA & NASS	.php	https://www.nass.usda.gov/Charts_and_Maps/
Crop Condition & Soil Moisture	Crop-CASMA	.gis	https://nassgeo.csiss.gmu.edu/CropCASMA/
Plant Diseases	Kaggle	.csv	https://www.kaggle.com/saroz014/plant-diseases
Soil Health & Characterization	NCSS	.mdb	https://new.cloudvault.usda.gov/index.php/s/7iknp275KdTKwCA
Pesticide use in Agriculture	USGS	.php, .txt	https://water.usgs.gov/nawqa/pnsp/usage/maps/
Water use in Agriculture	USGS	Tableau	https://labs.waterdata.usgs.gov/visualizations/water-use-15
Groundwater Nitrate Contamination	USGS	.jpeg	https://prd-wret.s3.us-west-2.amazonaws.com/assets/palladium/production/s3fs-public/thumbnails/image/wss-nitrogen-map-us-risk-areas.jpg
Disaster Analysis	USDA & NASS	.png, .pdf	https://www.nass.usda.gov/Research_and_Science/Disaster-Analysis/

storing these data can help study, train, and test to improve and impede the diseases in crops. Predicting plant diseases can enhance crop yield and productivity. Fig. 8.3 shows some sample images from the Pomegranate Fruit Dataset [220].

Fig. 24 shows some sample images from the Chinese Cabbage Disease dataset [221].

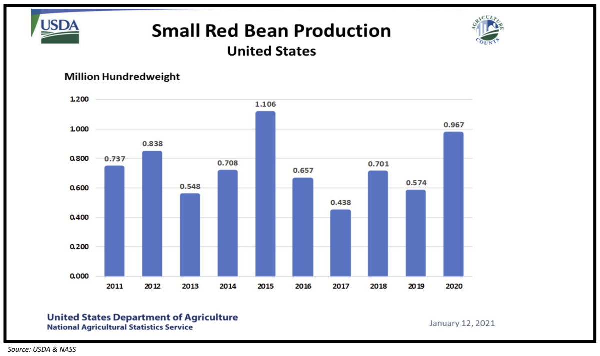
8.4 Soil Health and Characterization

The soil characterization survey is used to give information regarding the properties and features of soil in a specific area. The survey can contain detailed descriptions and soil boundaries that are beneficial to the farmers, estate agents, and engineers.

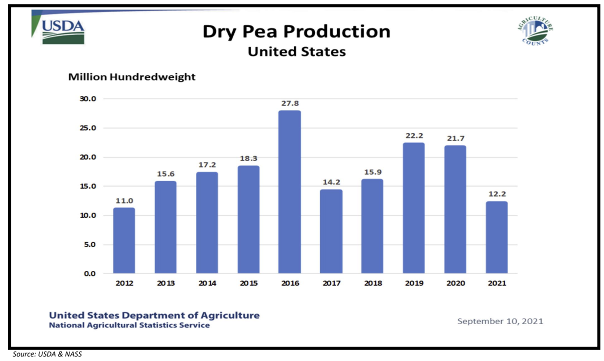
The National Cooperative Soil Survey (NCSS) provides database reports for soil classification [222] along with the pedon number for soil taxonomy. A pedon is a three-dimensional structure of soil that is sufficient to explain the soil's inner composition and can be used for collecting samples for lab analysis. The soil properties at each field, such as available rock fragments, bulk density, moisture, water content, carbon, salt, pH, carbonates, phosphorous, clay, sand, and silt mineralogy, can be obtained from the primary data characterization of the soil. The reports can be seen on-screen or downloaded in text files by giving primary country, state, and county details [222].

8.5 Pesticide Use in Agriculture

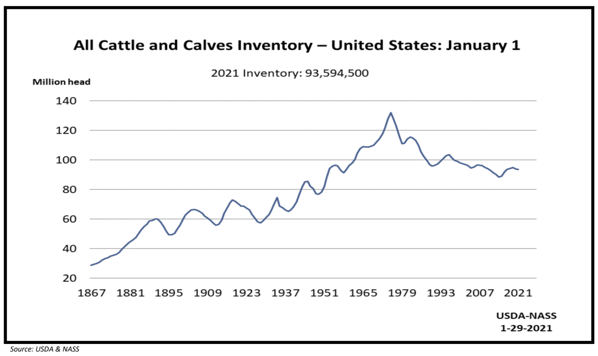
The primary use of pesticides in agriculture is for controlling weeds, insect infestations, and fungus. However, excessive use of pesticides can destroy other microorganisms necessary for soil health and degrade the quality of groundwater. The U.S. Geological Survey (USGS) collects data for the amount of pesticide used in the U.S. on an annual basis in the form of tables, graphs, and maps [223]. The map provides a more refined picture of estimated pesticide use on agricultural land in terms of pounds per square mile, and the graphs show the estimated usage in millions of pounds for each crop every year.



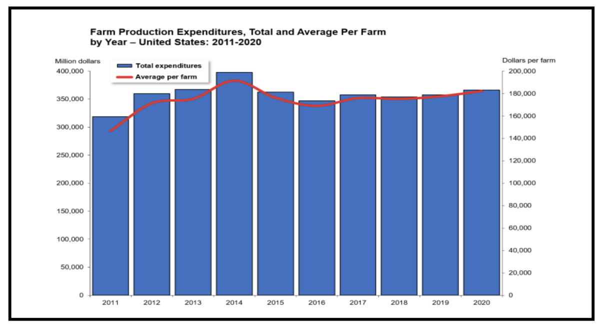
(a) Small Red Bean Production.



(b) Dry Pea Production.



(c) All Cows and Calves Inventory.



(d) Farm Production Expenditures.

Figure 20: Graphs showing Crop yield and Production [217].

8.6 Water Use in Agriculture

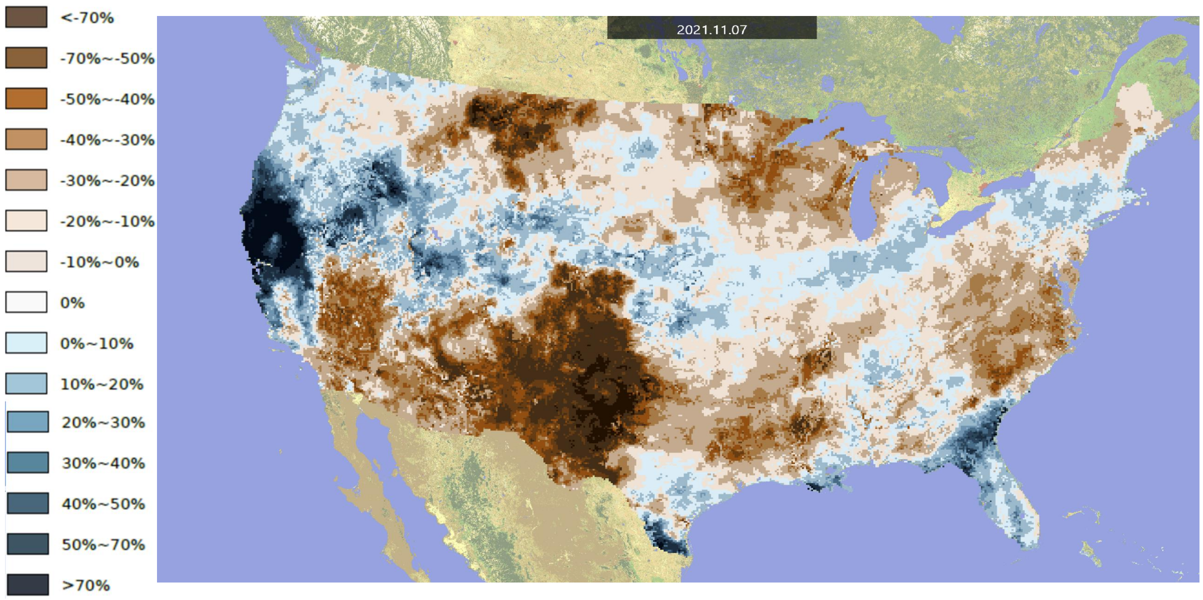
Water is essential for agriculture. Both surface and groundwater are crucial and are utilized in farming [224]. Surface water is formed from natural rivers and lakes; groundwater is found under the earth's surface between rock, soil, and sand cracks. The USGS collects total water usage every five years and updates the statistics in billions of gallons per day. The data shows that water use is higher in agricultural areas, including irrigation, livestock, and aquaculture [225].

8.7 Groundwater Nitrate Contamination

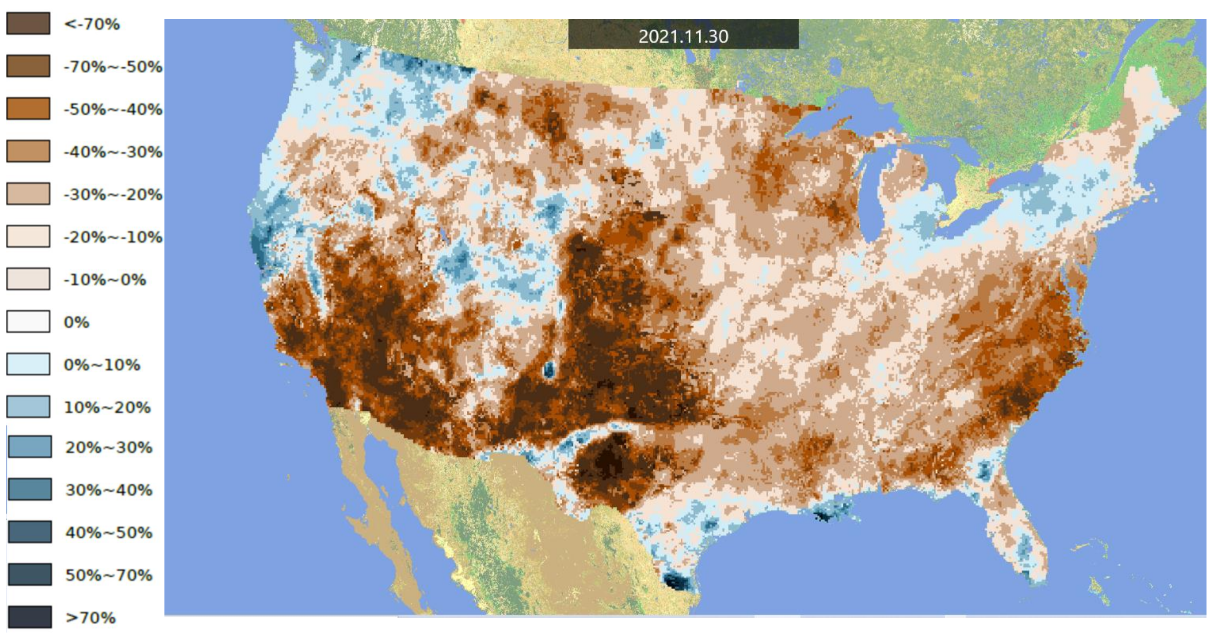
Nitrate is the primary source for the growth of plants and crops. It is an oxidized form of nitrogen, which occurs naturally in the earth, but it can dissipate due to extensive farming. To refill the soil with essential nutrients, nitrogen fertilizers are applied while farming. Nonetheless, these nitrates can be toxic primarily when they enter food, groundwater, and surface water. Fig. 25 shows the map for contamination of groundwater all over the United States. Collecting data nationwide, the USGS has developed a model for estimating groundwater nitrate contamination [226].

8.8 Disaster Analysis

Agriculture is facing threats from uncertain risks and changing landscapes and temperatures. It is necessary to forecast disasters before they occur to know the intensity of these hazards so farmers can be prepared for the worst and plan accordingly. The USDA and National Agricultural Statistics Service (NASS) have implemented a research study for disaster analysis assessments in near real-time. To collect the datasets, geospatial techniques and sensors are used in the procedure to estimate the disasters [227]. One of the example studies for monitoring flooding with the help of Sentinel-1, Synthetic Aperture Radar is given in [228].



(a) Dated November 07, 2021



(b) Dated November 30, 2021

Figure 21: Crop Condition and Soil Moisture in the United States [218].

(a) Healthy Plant Leaves - Apple, Potato, and Peach (From Left to Right)

(b) Infected Plant Leaves - Scab Infected Apple, Late Blight Infected Potato, and Bacterial Spot Infected Peach (From Left to Right)

Figure 22: Sample Images from Plant Disease Disease Dataset [219].

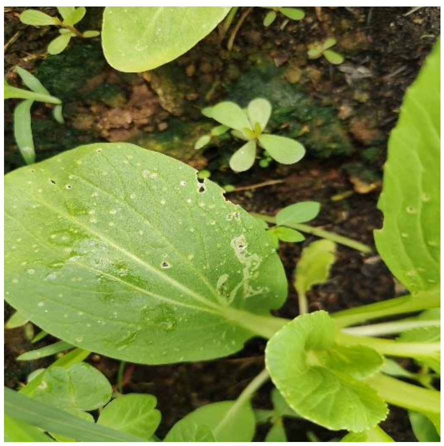
(a) Pomegranates of Different Grades of Quality 1 (From Left to Right - Grade 1, Grade 2, Grade 3)

(b) Pomegranates of Different Grades of Quality 4 (From Left to Right - Grade 1, Grade 2, Grade 3)

Figure 23: Pomegranate Fruit Dataset [220].

(a) Healthy Chinese Cabage Plant

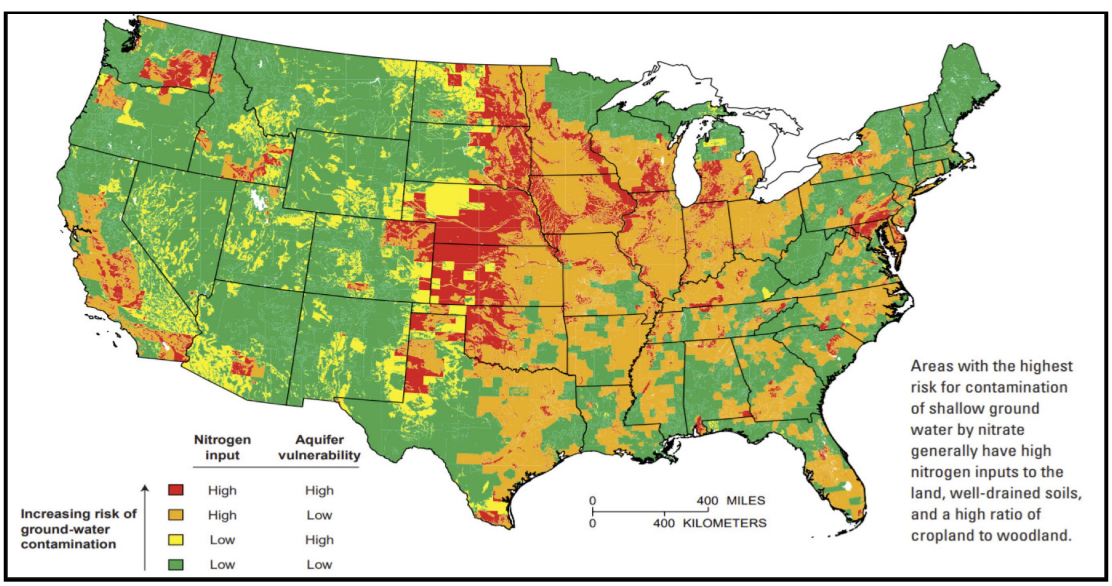
(b) Infected with Back Moth



(c) Infected with Leaf Miner

(d) Infected with Mildew

Figure 24: Chinese Cabbage Disease Dataset [221].



Source: United States Geological Survey(USGS)

Figure 25: Groundwater Contamination [226].

9 Smart Agriculture Open Research Problems

In this section we discuss the open research problems of *Agriculture* 4.0 and *Agriculture* 5.0. We can divide them into two main sub groups depending on the research focus.

9.1 Technology Perspective

Smart agriculture faces various challenges as previously mentioned. These challenges need to be addressed by adapting new and existing technologies. Until now most of the smart agriculture AI models were cloud based, cloud-edge based, or cloud-fog-edge based. Hardware advancement has boosted the computing paradigm shift. The addition of intelligence to IoT devices is the new trend [229]. Network availability, latency and bandwidth are not anymore barriers in successful, seamless agriculture system operations. This opens up a new avenue for research. Edge AI in smart agriculture is a broad area which will be a hot topic in the near future. Fig. 26 shows various open research problems in a technology context. Research in the following fields holds much promise:

- Low powered and solar powered, low latency TinyML devices.
- Low computational decision methods suitable for low powered IoT devices.
- Sensor technologies operable in extreme temperatures.
- Data analytic methods for data compression.
- Quantization and pruning techniques for AI/ML models.
- Unsupervised and semi-supervised learning methods.
- Real time data analysis and decision.
- Public dataset creation with sensor data.
- UAV taken image dataset.
- Thermal and Infrared image dataset for crop field.

Research areas are not only limited to these. Blockchain based data privacy and integrity and service based smart agriculture applications are other areas to work with:

- Blockchain enhanced IoT applications focusing on immutable data storage mechanisms.
- Optimizing computational resource, design time, and energy efficiency.

Hardware security is another broad area of research for sustainable Smart Agriculture. The functionality and applications of each IoT device in agriculture is unique. Research on PUF, which is a hardware fingerprint [230, 231] is an important area of research:

- PUF's susceptibility to environmental effects like rainfall, pesticides, fertilizers, and chemicals.
- Reliability and tamper resistance of these hardware security modules.

9.2 Network Perspective

The network component is a very important aspect of smart agriculture which makes use of different Information and Communication Technologies (ICT) to interconnect remote devices and make data transfer possible. Budding stage unsecured network layer protocols for limited resource IoT devices have led to various security threats. A classification of research problems which need to be addressed is given in Fig. 27.:

- Providing alternative networking paths which can operate during natural disasters.
- Techniques to increase the real-time data operations even when the network is experiencing congestion due to high volumes of transactions.
- Robust and resource efficient techniques are still needed to manage data privacy and security challenges.
- Efficient network topologies are needed to maximize usage of the available hardware and increase coverage area to avoid blind spots.
- Cost-efficient methods for easy maintenance of network equipment with minimal wear and tear can be challenging.

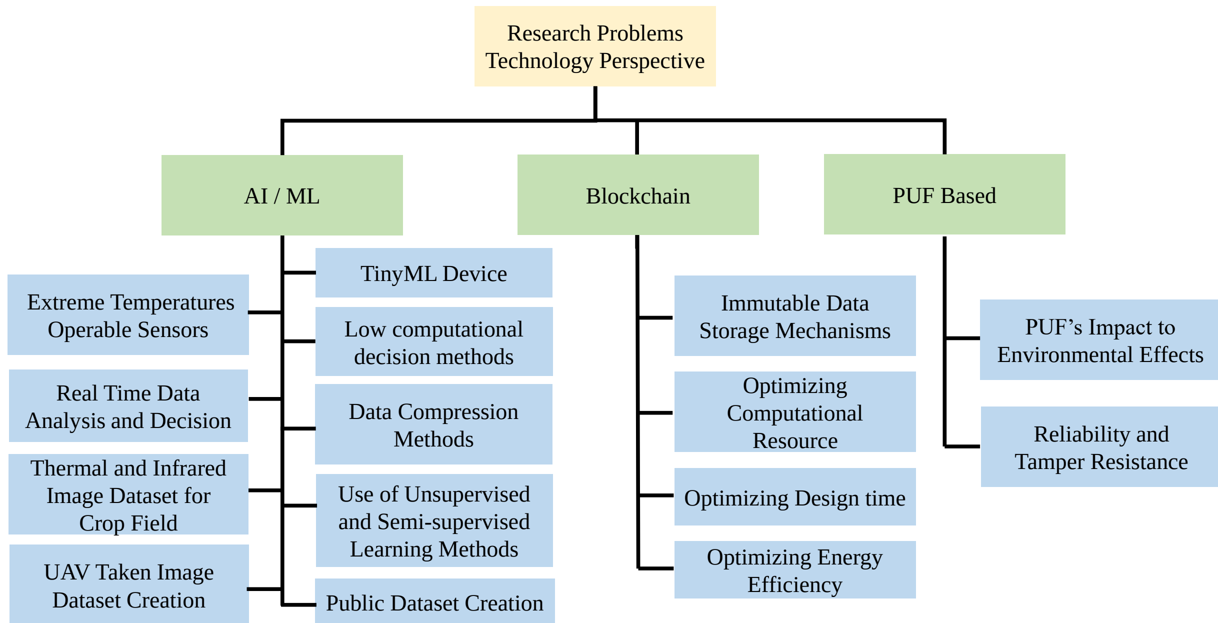


Figure 26: Network and Communication Challenges on Smart Agriculture.

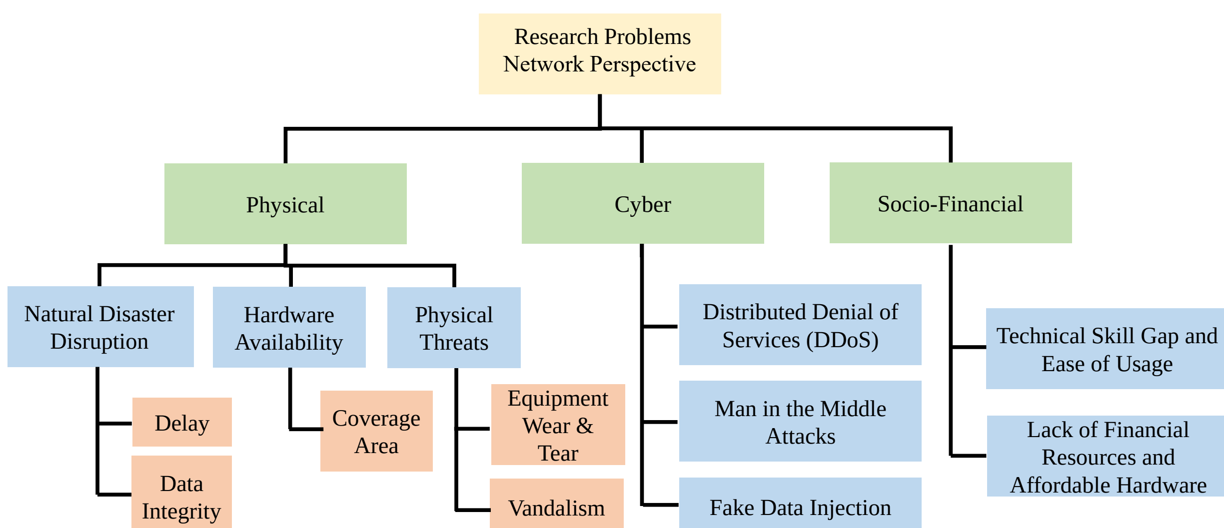


Figure 27: Network and Communication Challenges of Smart Agriculture.

- Preventive techniques to address physical damages like vandalism by adversaries are much needed.
- Proper routing techniques in the network to avoid network threats like DDoS can be an area of interest to work.
- Efficient encryption techniques and authentication mechanisms such as hardware assisted authentication are very much needed to be included in network layer to avoid different security threats.
- Ease of use and troubleshooting mechanisms can be areas of interest for researchers as this technology is developed for farmers.
- Network equipment is expensive, thus making networking hardware affordable can make the technology more adopted into vast applications in Smart Agriculture.

10 Conclusions and Future Directions

In today's world, we value more than ever "Let food be thy medicine" as quality food boosts our immunity. Research on agriculture, food security, and food supply chain has become more relevant. This article provides a detailed survey on the ongoing research trends in smart agriculture. It discusses recent technology trends to challenges and open research problems in this field. The authors believe this work will give an overall idea on technologies, challenges and research problems in smart agriculture.

Technological advancement along with rapid growth of ICT have transformed traditional agriculture to a smart, intelligent, automated agriculture. Smart agriculture reduces the carbon footprint by introducing sustainable, green farming, reducing the use of pesticides and fertilizers, and optimizing the use of natural resources. Soon the agricultural industry will welcome Agriculture 5.0 [232]. This will raise yields while keeping the system environmentally sustainable. Developing countries will also follow the same trend as developed countries. Humanity will embrace the production and distribution of food in an economically and ecologically efficient way as never before [233].

List of Acronyms

A-CPS Agricultural Cyber-Physical Systems . . . 7
ANN Arificial Neural Networks . . . 7
AI Artificial Intelligence . . . 1
BD Big Data . . . 2
BRT Boosted Regression Trees . . . 17
CNN Convolutional Neural Networks . . . 15
CFS Correlation-based Feature Selection . . . 18
Crop-CASMA Crop Condition and Soil Moisture Analytics . . . 23
CPS Cyber-Physical Systems . . . 7
DDoS Distributed Denial-of-Service . . . 21
DLT Distributed Ledger Technology . . . 1
DNN Deep Neural Networks . . . 17
DoS Denial-of-Service . . . 20
EDC Edge Data Centers . . . 20
EPCIS Electronic Product Code Information Services . . . 22
ERP Enterprise Resource Planning . . . 22
FL Fuzzy Logic . . . 7
GPRS Ground Penetrating Radar Services . . . 6
GPS Global Positioning System . . . 10
GRU Gated Recurrent Unit . . . 17
H-CPS Healthcare Cyber-Physical Systems . . . 7
ICT Information and Communication Technologies . . . 29
IIoT Industrial Internet of Things . . . 11
IoAT Internet of Agro-Things . . . 7
IoMT Internet of Medical Things . . . 7
IoT Internet of Things . . . 2

IPFS Interplanetary File System . . . 23
LPWAN Low-Power Wide Area Network . . . 15
LSTM Long Short-Term Memory . . . 17
LTE Long-Term Evolution . . . 6
M2M Machine-to-Machine . . . 14
MAC Media Access Control . . . 23
ML Machine Learning . . . 1
MLP Multi-Layer Perceptrons . . . 17
NB-IoT Narrowband IoT . . . 6
NASS National Agricultural Statistics Service . . . 25
NCSS National Cooperative Soil Survey . . . 24
NFC Near Field Communication . . . 6
NVDI Normalized Difference Vegetation Index . . . 10
P2P Point-to-Point . . . 17
PBFT Practical Byzantine Fault Tolerance . . . 21
PoS Proof-of-Stake . . . 20
PoW Proof-of-Work . . . 20
PUF Physical Unclonable Functions . . . 1
RFID Radio Frequency Identification . . . 6
RMSE Root Mean Square Error . . . 18
RNN Recurrent Neural Network . . . 18
RPN Region Proposal Network . . . 17
SDN Software-Defined Networking . . . 21
SIL Solar Insecticidal Lamps . . . 14
SPoF Single Point-of-Failure . . . 19
SSD Single Seed Descent . . . 18
SVM Support Vector Machines . . . 14
UAV Unmanned Aerial Vehicles . . . 2
USDA U.S. Department of Agriculture . . . 23
USGS U.S. Geological Survey . . . 24
WSN Wireless Sensor Network . . . 5

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