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A survey on the role of Internet of Things for adopting and promoting Agriculture 4.0

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ABSTRACT

There is a rapid increase in the adoption of emerging technologies like the Internet of Things (IoT), Unmanned Aerial Vehicles (UAV), Internet of Underground Things (IoUT), Data analytics in the agriculture domain to meet the increased food demand to cater to the increasing population. Agriculture 4.0 is set to revolutionize agriculture productivity by using Precision Agriculture (PA), IoT, UAVs, IoUT, and other technologies to increase agriculture produce for growing demographics while addressing various farm-related issues. This survey provides a comprehensive overview of how multiple technologies such as IoT, UAVs, IoUT, Big Data Analytics, Deep Learning Techniques, and Machine Learning methods can be used to manage various farm-related operations. For each of these technologies, a detailed review is done on how the technology is being used in Agriculture 4.0. These discussions include an overview of relevant technologies, their use cases, existing case studies, and research works that demonstrate the use of these technologies in Agriculture 4.0. This paper also highlights the various future research gaps in the adoption of these technologies in Agriculture 4.0.

1. Introduction

The world population is expected to rise 31% by 2050, and with that, the required usage of natural resources and food production will also grow. 71% more resources will be required in the subsequent three decades due to this increase in the population (Ayaz et al., 2019). The increase in global population requires us to move from traditional farming practices to modern techniques of Agriculture 4.0. Agriculture 4.0 is the next phase in sustaining the continuously increasing population of the world. It includes concepts like automatic tractors, Precision Agriculture, and IoT to measure agriculture in profound novel ways quantitatively. Agriculture 4.0 renders an increase in yields with a lower input cost, labor and environmental pollution, in this current time of rising demand for food (Shirish and Bhalerao, 2013). Agriculture 4.0 has been one of the top ten agricultural revolutions since the 1990s (Crookston, 2006). Agriculture 4.0 improves the organization of farm inputs (such as fertilizers, fuel, seeds and herbicides) through distributed management practices. Agriculture 4.0 partitions large fields into zones where each zone receives customized management inputs based on the specific location, soil type, and management records, historically receiving standardized administration of irrigation, fertilizers, seeds, and other farm inputs. Thus, with better management of agricultural inputs, Agriculture 4.0 aims to revolutionize crop production and farm profitability.

A dramatic surge in the utilization of modern computers and electronic technologies is expected owing to present-day food production and PA (Cho et al., 2012). The evolution of information and communication technology (ICT) has led to the advent of two essential concepts that have a significant global impact: Internet-of-Things (IoT) and Cloud Computing (Evans, 2011). Both concepts are used in Agriculture 4.0 and are expected to be utilized on a massive scale in the near future.

For the intent of research and development in the field of precision and environmentally sustainable agriculture (Popović et al., 2017), an IoT-based cloud platform can be used. Such projects can focus on the

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implementation of a sustainable agriculture research and development network for crop monitoring, forest and water monitoring, the development of emission control and mitigation strategies, food textcolorblueanalysis and quality control, land quality management as well as enhanced healthcare.

IoT's highly integrated, extensive, all-embracing, and open nature is ideal for smart agriculture (Gershenfeld et al., 2004). IoT smart agriculture platform offers integration of automation equipment from various organizations. These types of equipment are readily compatible with the smart system of the farm and facilitate data exchange among disparate elements and provide automation capabilities through standard internet practices. textcolorblueKamilaris et al. (2016), proposed Agri-IoT (Fig. 3) as a highly customized IoT-based online platform for creative data analytical solutions influenced by these advantages and the possibilities of IoT for smart farming, considering the lack of absolute, effective, well-established solutions and framework. Agri-IoT allows for comprehensive, automated data processing and analysis based on real-time data streams from a wide range of sources, including sensory systems, security cameras, high-speed images from drones, online weather forecasting services, social media streams for rapid event detection, e.g., threats, floods, earthquakes, and information, notifications, and alerts from government agencies (Hassija et al., 2019). Agri-IoT assists farmers by integrating and analyzing data streams like those described above, in their decision-making processes in almost real-time through immediate response to changes and unexpected events.

Agriculture 4.0 makes use of many modern technologies like Remote Sensing (RS), Machine Learning (ML), Big Data, Deep Learning, Thermal Imaging and UAVs. Agriculture 4.0 provides a full-stack system consisting of Remote Sensors, Wireless Sensor Networks (WSN), virtualization systems, cloud computing, and end-user applications. Remote sensing (RS), to minimize operational expenses and environmental hazards, and to increase production, is being used more extensively in designing decision support tools for modern farming systems. The processing of vast volumes of remotely sensed data from different systems is one of the key criteria of remote sensing-based solutions, leading to an increase in the research on machine learning (ML) methods. Machine-based learning systems are capable of managing a wide variety of inputs and nonlinear operations.Throughout the evolution of smart farming, the use of ICT is emphasized in the cyber-physical agricultural management process. New technologies, such as the IoT and cloud computing, are expected to exploit this growth to incorporate more robots and artificial intelligence in agriculture. This phenomenon is found in Big Data which consists of large data collections with a wide variety that can be documented, analyzed and used for decision making. The purpose of this survey is to gain insight and recognize the related socio-economic and technical problems in the state-of-the-art of smart farming big data applications. Deep learning provides a new, modern imaging and database analysis technology that offers promising results and great opportunities. Due to the productive applications of deep learning in different fields, it has recently entered the agriculture sector. We study in this survey the similarities in terms of class or regression variations, between deep learning and other existing common techniques. Remote sensing using UAVs in Agriculture 4.0, which not only provides an unrivaled spectral, spatial, and temporal resolution, but also gives details of vegetation height and multiangular observations. The developments in UAVs have increased the chances of understanding the in-depth variability of crop and soil conditions that are useful for different agronomic decision-making. They have made spatial and temporal imagery possible at low costs. This survey focuses on existing and future applications and challenges of thermal remote sensing within Agriculture 4.0. We also present the recent developments in the field of the Internet of Underground Things (IoUT), which emphasizes the potential of technologies for communication, networking and textcolorbluelocalization concerns. IoUT includes underground objects (sensors), technologies of communication, and networking protocols. For various industries, such as oil and gas, forestry, seismic mapping, and boundaries, IoUT facilitates the incorporation of sensing and communication into the underground environment. Such applications gather important information from the underground things that are deployed. This survey analyzes and discusses state-of-the-art communication technologies and applications of IoUT.

1.1. Our contributions

Though few works discuss the use of the emerging technologies discussed in the Introduction for Agriculture 4.0, none of them comprehensively addresses all of the technologies. Here, we present the various components of Agriculture 4.0. The key contributions of our survey are as follows:

1. An insight into the domain of Agriculture 4.0, the technologies supporting it, and its various applications are provided.
2. This comprehensive survey discusses the various IoT devices and equipment, and different communication technologies that are deployed in Agriculture 4.0.
3. The applications of UAVs and thermal remote sensing in Agriculture 4.0 have been discussed in detail.
4. The survey discusses IoUT, a novel class of IoT, the various IoUT systems available, and the major challenges faced in the deployment of these systems.
5. The conceptual framework of Big Data in smart farming has been discussed.
6. The Machine Learning approaches for yield estimation and nitrogen precision in agriculture have been discussed in detail.
7. The applications of Deep Learning in agriculture, its advantages as well as its limitations have been discussed.
8. Furthermore, challenges and future trends in the field of Agriculture 4.0 have also been discussed.

1.2. Survey outline

The rest of the paper is organized as follows. In Section II, the importance of Agriculture 4.0 and PA is discussed along with the role of IoT in Agriculture 4.0, key technologies involved in agriculture 4.0, and efficiency of Agriculture 4.0 to tackle the growing challenges of food demand and sustainability. Section III provides an overview of the types of UAVs employed for different tasks in the agricultural sector and the applications of thermal remote sensing in farming. A review of the various IoUT solutions available and how they enable the information from the agricultural fields to be transmitted to the cloud for real-time decision-making is presented in Section IV. Section V talks about data-driven agriculture and the extraction and analysis of data to get results. In Section VI, an overview is given of the various features of Machine Learning technologies that make them extremely useful and relevant to Agriculture 4.0. An analysis of the related work and numerous applications of Deep Learning in agriculture has been done in Section VII. Section VIII summarizes the open research challenges and future trends to be expected in the field of Agriculture 4.0. Finally, the paper is concluded in Section IX. To convey a clear presentation, the organizational structure of the paper is exhibited in Fig. 1. A glossary regarding the used abbreviations and acronyms is listed in Table 1 to provide guidance along this paper's reading.

2. Use of IOT in agriculture 4.0 and key technologies involved

Agriculture 4.0 addresses agricultural production challenges in terms of efficiency, environmental effects, food security, and sustainability (Gebbers and Adamchuk, 2010). As the world's population is rising steadily (Kitzes et al., 2008), food production needs to rise considerably ("O and 2009. How to Feed t, 2009), while preserving availability and high nutritional quality worldwide. Agriculture 4.0 tracks land quality,

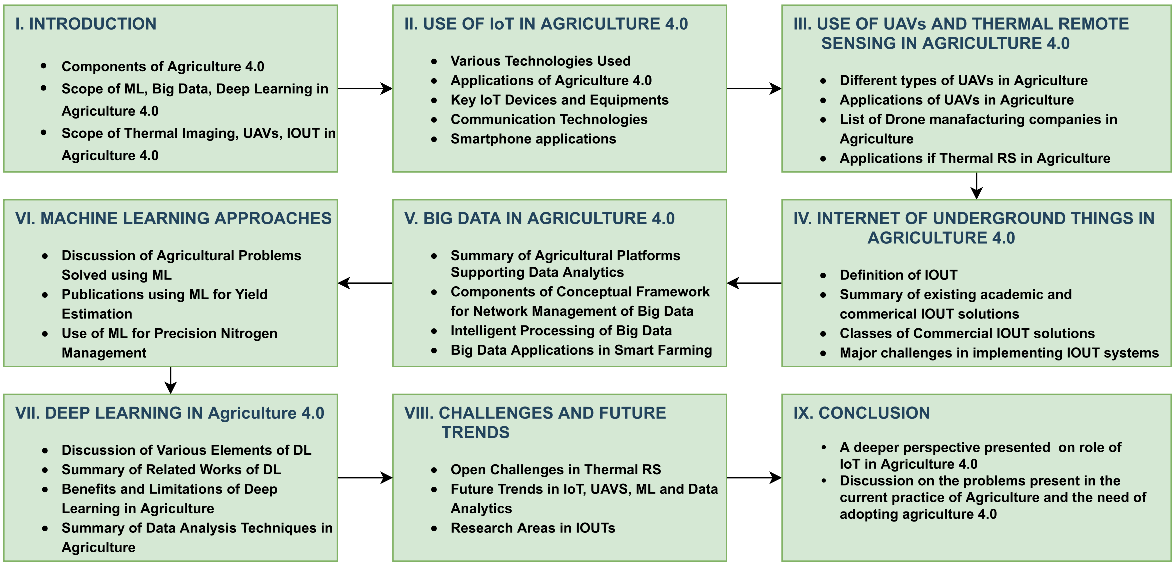

Fig. 1. Graphical representation of the organization of the survey.

maximizes profits, and minimizes effects on the environment by automating all the processes in agriculture. IoT has helped open an effective approach for smart farming and agriculture. Fig. 2 lists a few use cases of Agriculture 4.0. Smart irrigation, smart soil fertilization, smart pest control, identification of plant diseases (Sekulic and Djurovic, 2016; Jhuria et al., 2013) are aspects of such consumer end-use applications. For instance, a smart sprinkler system is critical in predicting grapevine downy mildew (Plasmopara viticola) since the disease causes severe damage in Montenegro's vineyards annually. In the past, this disease has resulted in a complete production loss for several years. Thus, smart systems have been invented to enable grapevine growers to properly assess the correct period for treating the vines with appropriate fungicides.

Fig. 3 displays the platform for Agri-IoT data analytics. It is composed of several layers, the lower (device, planes of communication), the mid-level (data, data analytics) and the higher (application, user-end planes). Different components of software include various data collection, modeling, evaluation or simulation operations in each layer. Each component of the software is regarded as a single entity with its open API and can, thus, make a scalable distributed architecture where applications can include different layer components based on their particular requirements. It leads to the use of the various components as plug and play and can be exclusively used according to the specifications of a particular agricultural deployment.

2.1. Framework of agriculture 4.0

In order to enhance efficiency in all business sectors (Sisinni et al., 2018; Ayaz et al., 2017; Lin et al., 2017a; Shi et al., 2019; Elijah et al., 2018), IoT has started influencing a diverse range of domains and enterprises, spanning from manufacturing and construction to public health and safety, communications systems, and power and energy to the farming sector. This has been achieved by the features of IoT, such as an effective communication framework that is used to interact with smart devices from sensors, cars, smart phones, etc. The communication is done by making use of the Internet, and several services such as regional or distributed data collection, intelligent cloud-based information processing, and decision-making, user interfaces and automated farm operations. Fig. 4 highlights the significant hurdles of technology implementation in Agriculture 4.0.

The range of technologies involved in Agriculture 4.0 solutions design and delivery is quite extensive and multidisciplinary ("Enabling The Smart Agric, 2016). This diversification often involves the participation of various industry players including providers of telecommunications services, manufacturers of agricultural equipment and vehicles, software engineers, data analyzers, and vendors of sensing technology. The survey discusses a set of smart agricultural technologies as shown in Fig. 5. Together, all these technologies correspond to four crucial steps in smart agricultural projects: Data Sensing, data collection, transmission of data and processing data.

2.1.1. Data sensing and data collection

All smart farming practices are inspired by sensing technology. Whether the data is collected from a soil sample or satellite corrective signals, it is the key foundation for all applications. For instance, the collected datasets may illustrate both spatial and temporal variations in an area. Sensor technology applications include the monitoring of soil health, livestock sensing, tanks and silo level sensing. The arrangement of field sensors and devices is customized to the data type required. There must be educated choices made as to:

- the location of sensors and gateways and the quantity required onsite
- how often data is gathered
- the data-payload size
- if a supply of power (battery or solar energy) is needed

2.1.2. Transmission of data

The data collected and registered via sensors are forwarded to the farm management information system using a variety of communication modes in all agricultural applications that use remote monitoring. Wireless communications–2G to 4G–is the most preferred mode. In rural areas, there can be very low availability and dependability of mobile connectivity. Hence, satellite data communication may be an alternative. Satellite costs can, however, be outrageously high for medium and

Table 1
List of abbreviations used in the paper.

AI	Artificial Intelligence	MI	Magnetic Induction
ANN	Artificial Neural Network	ML	Machine Learning
BLE	Bluetooth Low Energy	MLR	Multiple Linear Regression
BN	Bayesian Networks	NDIR	Non Dispersive Infrared
BPNN	Back-propagation Neural Network	NDVI	Normalized Difference Vegetation Index
BRT	Boosted Regression Trees	NDWI	Normalized Difference Water Index
CNN	Convolutional Neural Networks	NIR	Near Infrared
CPANN	Counter Propagation Artificial Neural Networks	OEM	Original Equipment Manufacture
CWSI	Crop water stress index	OTA	Over-The-Air
DL	Deep Learning	PA	Precision Agriculture
DP	Dirichlet Processes	PASCAL VOC	PASCAL Visual Object Classes
DRNN	Deep Recurrent Neural Network	PBI	Picture Based Insurance
DT	Decision Trees	PLS	Partial Least Squares
EM	Electromagnetic	PLSR	Partial Least Squares Regression
ET	Evapotranspiration	PM	Process Mediated
EVI2	2 band Enhanced Vegetation Index	PSO	Particle Swarm Optimization
FAO	Food and Agriculture Organization	PVI	Perpendicular Vegetation Index
FCM	Fuzzy Cognitive Maps	QoS	Quality of Service
FMIS	Farm Management Information System	RF	Random Forests
GIS	Geographic Information System	RFRK	Random Forests Residuals Kriging
GPS	Global Positioning System	RMSE	Root Mean Square Error
GVI	Green Vegetation Index	RS	Remote Sensing
HS	Human Sourced	SAVI	Soil Adjusted Vegetation Index
IBP	Indian Buffet Process	SKN	Supervised Kohonen Networks
ICT	Information and Communication Technology	SNB	Stagonospora nodorum blotch
IoT	Internet of Things	SOM	Self Organizing Maps
IoUT	Internet of Underground Things	SR	Simple RatioIndex
IR	Infrared	SVM	Support Vector Machines
ISM	Irrigation System Management	SVR	Support Vector Regression
IT	Information Technology	UAV	Unmanned Aerial Vehicles
KNN	K-Nearest Neighbours	UG	Underground
LAI	Leaf Area Index	UT	Underground Thing
LPWAN	Light Power Wide Area Network	VF	Vertical Farming
LS-SVM	Least-Squares SVM	VI	Vegetation Index
MCWSI	Modified Crop Water Stress Index	WAN	Wide Area Network
MG	Machine Generated	WSN	Wireless Sensor Network

small-sized businesses. Furthermore, some farms need long-term battery-life devices with low data costs. In these cases, it can be expensive even if a 2G connectivity is provided. The Light Power Wide Area Network (LPWAN) is believed to be a possible replacement for obtaining extended battery-life cell connectivity, high-range connectivity scenarios and affordable rates. The management of crops and pastures are two applications that are currently served through LPWAN networks.

2.1.3. Farm management information system (processing data)

The sensed and collected data is sent to the Farm Management Information System (FMIS), often known the back office. The FMIS gathers data from interconnected farming operations, as well as a multitude of data from experience, which includes environmental events, weather patterns, economics, product requirements, system settings, etc. In an attempt to make the right decision, FMIS assesses all of this data together. For a specific application, the FMIS must be designed uniquely. Software engineers are required to receive information from people with expert knowledge of the product: veterinarians, plant researchers, pests and rodents scholars and other specialists in agriculture. This data is essential to ensure the best use of the technologies and processes for gathering and evaluating the right data for the right applications and understanding the results.

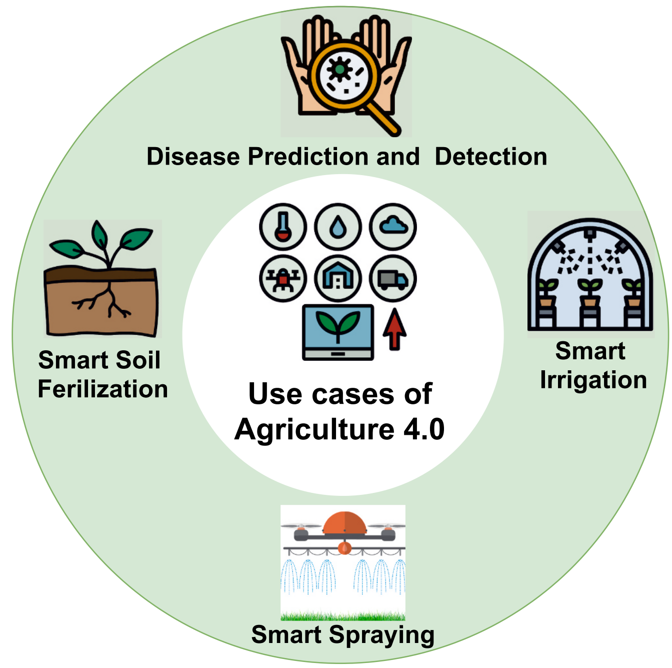

Fig. 2. Agriculture 4.0: High-level use cases.

2.2. Applications of agriculture 4.0

IoT is capable, through the practice of smart agriculture, of developing solutions for several conventional agricultural issues such as drought response, yield enhancement, irrigation and pesticide regulation. Fig. 6 identifies a list of primary smart agriculture services, applications and wireless sensors. In addition, significant scenarios wherein these technologies help to improve the overall performance at different phases are addressed below (Ayaz et al., 2019).

2.2.1. Soil sampling and mapping

This is one of the very preliminary steps, and involves soil sampling to collect information specific to the field. This can then be used at several decisive stages to make better choices. The primary purpose of soil analysis is to assess the status of nutrients in a region, to take measures in accordance with deficiencies in nutrients. Extensive soil testing, mainly in the spring, is suggested yearly, but it may be carried out in autumn or winter, depending on soil and climate conditions (Dinkins and Jones, 2013). Soil mapping opens up opportunities in a field that corresponds to the soil properties to seed, seed suitability, time to sow, or seed depth.

2.2.2. Irrigation

Nearly 96% of the water on earth that is contained in oceans is salt water. The 4% that remains constitute the fresh water, of which two-third is frozen as polar ice caps (“”Ice et al., 2020; “”What Percent Of Earth I, 2020). Merely 0.5% of the fresh water that is not frozen lies on the earth’s surface or in its atmosphere. The rest remains beneath the ground. In essence, mankind is dependent on this 0.5% to fulfill every one of its needs and to sustain the ecosystem, since sufficient fresh

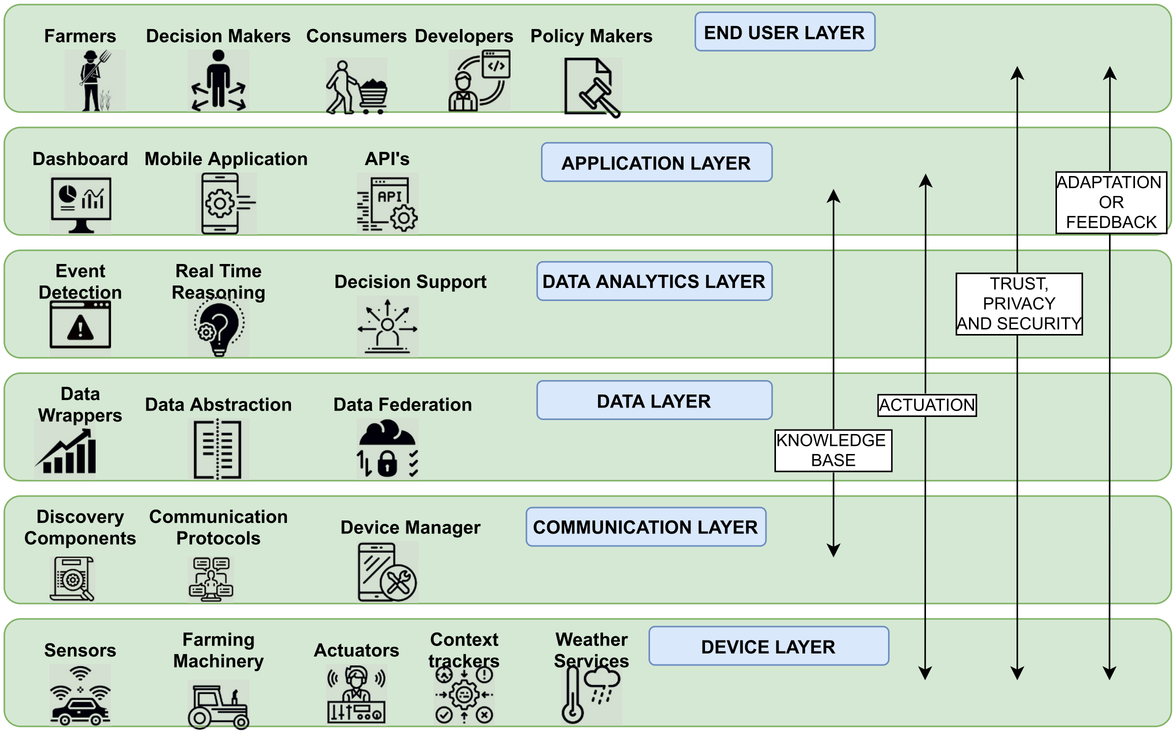

Fig. 3. Layered architecture of Agri-IoT ecosystem.

waters from lakes, rivers, and other types of reservoirs are required to maintain them (“”What Percent Of Earth I, 2020). Hence, it is important to realize, roughly 70% of this obtainable fresh water is used by farming alone. Diverse regulated irrigation methods are promoted to address water loss problems, including sprinkler and drip irrigation methods. The lack of water adversely affects the quantity and quality of crops. Irregular or even unnecessary irrigation contributes to reducing soil nutrients and triggers microbial infections. Approximating the water needs of a farmland is difficult since different variables are involved, such as crop size, irrigation process, soil quality, precipitation, and the retention of soil moisture. Factoring this assumption, an accurate soil control as well as moisture control framework with wireless sensors can optimize water use and also improve crop health.

2.2.3. Fertilizers

Fertilizers can be organic or synthetic, and they support plant growth and fertility by providing essential nutrients and minerals. Any imbalance in nutrients and their inappropriate use can be severely damaging to plant health. Overuse of fertilizers has adverse effects on the land and the atmosphere due to the diminished quality of the soil and contaminated surface water, impacting the global climate. Smart agriculture fertilization accurately predicts the required nutrient dose, mitigating any adverse environmental consequences. Fertilization requires location-specific estimates of the level of nutrients in the soil based on different factors, including crop size, soil quality, soil absorption ability, product yields, fertility rate, etc.

2.2.4. Management of crop disease

In 1950, the Great Famine (Irish Potato Hunger) was triggered by a loss in the crops and a decrease in yields due to the outbreak of “potato blight”. Unfortunately, even now, corn cultivators in the United States and Southern Canada face an economic loss of about $1 billion because of the “southern leaf blight” disease (Bruns, 2017). The Food and Agriculture Organization (FAO) reports that a range of 20–40 percent of the total agricultural productivity is lost every year owing to pests, insects and diseases. Pesticides and several other agrochemicals are now a significant part of agriculture. Many of them are harmful to human and animal welfare and have a serious and permanent effect on the climate, causing substantial damage to complete ecosystems (Carvalho, 2017; Waskom et al., 1995). IoT-based smart devices such as wireless sensors, drones, robots, etc., enable farmers to substantially reduce the use of pesticides by systematically targeting cultivation adversaries. Advanced IoT-based pests and insect control offer accurate tracking, simulation, disease prediction and thus is more efficient than conventional pest control calendars or prescriptions (Venkatesan et al., 2018).

2.2.5. Greenhouse farming

The oldest form of smart farming is Greenhouse farming. Indoor crops are indeed relatively less adversely impacted by the surroundings and can also receive light other than daytime. Consequently, the crops which could be cultivated only in certain environments or in certain parts of the globe can now be cultivated anyplace and anytime. Many factors, such as the precision of monitoring parameters, structure of the hedge, material covering wind control impact, the decision support system, make the production of different crops in such regulated environments possible. Precise environmental parameter monitoring that involves many measuring points are considered, and many farm-related variables are to be regulated to maintain the local environment. This is the most critical activity in urban greenhouses.

2.2.6. Vertical farming

In the interest of satisfying the increasing requirements for food, the earth must have more arable land, but the fact is that one-third of this agricultural land has been lost due to deforestation and contamination over the last four decades (Cameron et al., 2015). Sadly, the consistency of the soil is compromised faster than nature can regenerate. This is due to the existing farming techniques built on industrial agriculture. Besides, agriculture only uses 70% fresh water, which might further pressurize available finite reservoirs of water. The problem for both land and water scarcity can be resolved by vertical farming (VF). VF gives us the chance to store the plants in a much more contained environment, which decreases the intake of the resources considerably. The yield can

Fig. 4. Major hurdles in technology implementation for Agriculture 4.0.

be enhanced several times using this method because it only needs a limited portion of the ground area compared with conventional farming practices. Edinburgh Sensors specifically engineered Boxed Gascard with the aid of a semi-dual beam Non-Dispersive Infrared (NDIR) system to augment the strength and lessen the ocular difficulty.

2.2.7. Hydroponic

Hydrophonic is a special hydroculture's branch wherein crops are cultivated devoid of soil to increase greenhouse farming benefits. Hydroponic is premised on a method of irrigation, in which the roots of the crops reside in a solution of dissolved nutrients or the roots are sustained by perlite and gravel. For this application, an exact nutrient estimation is critical. Hence an extremely reliable wifi control system is developed for tomato-hydroponics (Ibayashi et al., 2016), concentrating on various guidelines of communication, least influenced by the existence and growth of plants.

2.2.8. Phenotyping

Phenotyping is based on the latest crop technology that integrates plant genomics with their ecophysiology and agronomy. Research analysis in (Tripodi et al., (2018)) has concluded as plant phenotyping will be useful for examining the quantitative characteristics like plant growth, production quantity and quality, and the ability to deal with diverse strains. Additionally, the importance of sensing technology and photo-based phenotyping is demonstrated in (Rouphael et al., (2018)), which explains how such technologies can facilitate improvements not only to screen various biostimulants but also to understand how they function.

2.3. Key technologies and equipments used in agriculture 4.0

IoT devices involve embedded systems that communicate with actuators and sensors and allow wireless access. Often these IoT devices

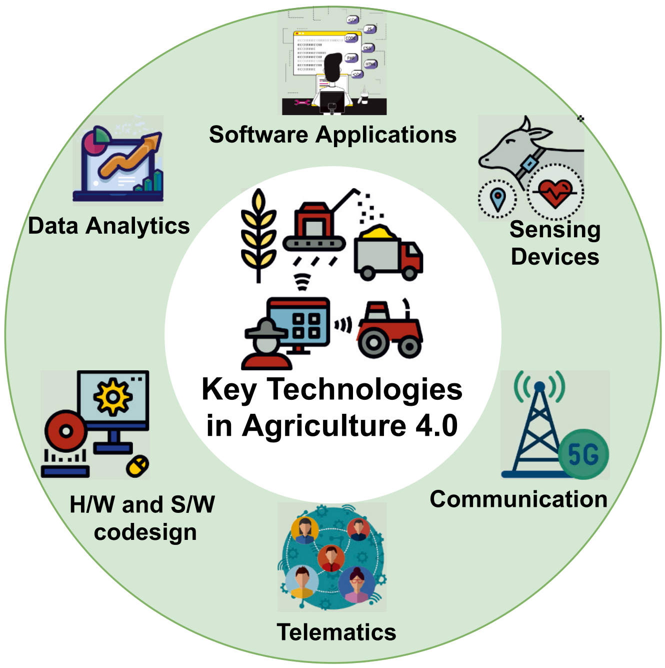

Fig. 5. Key technologies in agriculture 4.0.

are labelled IoT sensors. The sensors are utilized in tracking and assessing various farm variables, including nutrients of soil, meteorological information, and growth factors. IoT devices for agriculture are defined mainly by: energy efficiency, storage, portability, computational power, robustness, reliability, cost. These sensors are categorized into location, optical, electrochemical, airflow, and mechanical sensors (Li et al., 2010). The sensors gather data like air and soil temperature at different heights, leaf wetness, precipitation, wind speed, intensity and direction, relative moisture, solar radiation and air pressure. Fig. 7 gives a summary of the characteristics and functions of some of these sensors.

Modern agriculture primarily uses massive and sophisticated equipment like harvesters, robots, and tractors, entirely or partly assisted by remote sensing and other technologies of communication, to perform majority of operations. Agriculture 4.0 success depends on the exactness of the data collected, which is generally done by two methods (Zhang et al., 2018). The first method involves the use of multifunctional imaginative systems containing remote sensor platforms, like agricultural aircrafts, satellites, and UAVs. The second method concerns various sensor types, which can be used in numerous areas of interest for specific applications. The data collected is then classified using Global Positioning System (GPS) technology for precisely identifying the position of data so that treatment can be given at a later point in time. The following are the leading equipment and technologies available in the market for the above purpose.

2.3.1. IoT-based tractors

As a result of the growth of the agricultural industries, the rural labour force started straining under pressure, so tractors and other heavy automated machines came to be used in agriculture. Any typical tractor operates at a substantially reduced cost and 40 times faster than conventional farm labor. Agricultural equipment manufacturers, like John Deere, Hello Tractors, have begun offering better alternatives, such as automatically powered tractors as well as cloud computing facilities to meet the ever-increasing demands(Ayaz et al., 2019). A major benefit of these self-driven tractors is that they cannot revisit the very same region or rows, distanced less than one inch. This facility improves accuracy and reduces errors, particularly when insecticides are sprayed. Hello Tractor has built a significantly low cost tractor monitoring unit with computationally intense software and tools that can be mounted onto any tractor. This device ensures that the cost of the tractor stays economical for a large number of farmers while also tracking the tractor condition and reporting the occurrence of any issues.

2.3.2. Harvesting robots

Harvesting the crop at the appropriate time is of utmost necessary, since being early or late will greatly affect the yield. In the past few decades, the involvement of robots has risen for automating and creating the harvesting mechanism more specific. Intensive study has been carried out by several researchers to refine the responsiveness of robot services for fruit sensing in terms of its size, shape, colour, and location (Zhao et al., 2016; Zujevs et al., 2015; Bargoti and Underwood, 2017; Bac et al., 2017). The desired intention is to identify the various fruits in their natural habitat even if they are partly or completely occluded by the leaves or intermixed with some other fruits (Feng et al., 2019). Having more than sixty different sizes, shapes, and colours for just a pepper itself, very customized and technically advanced tools are therefore required for distinguishing the different conditions of fruits

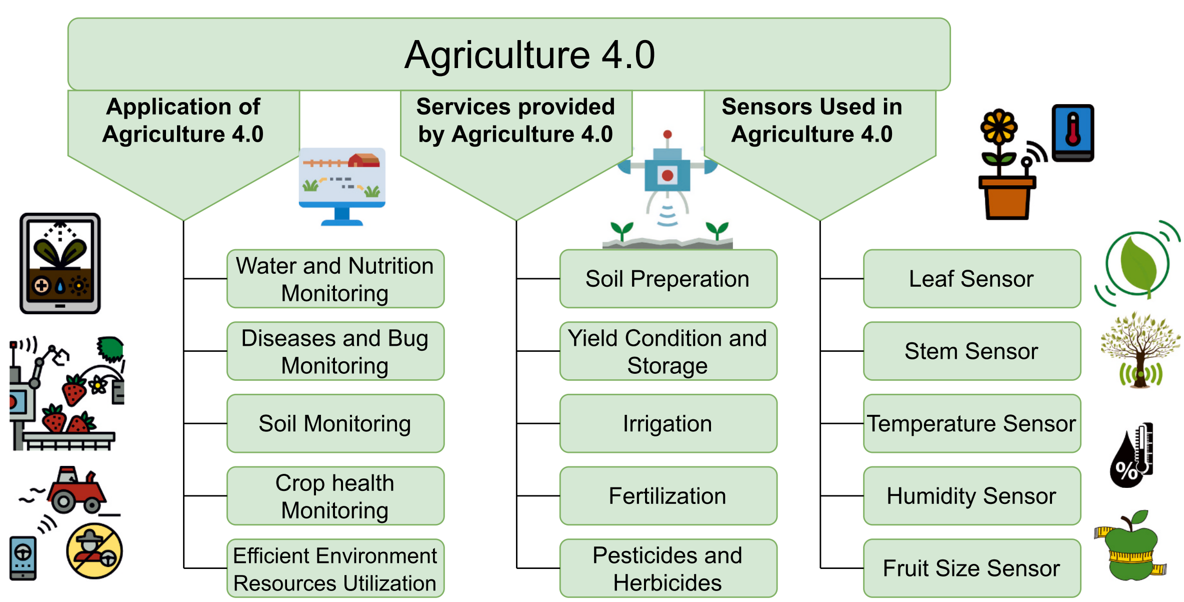

Fig. 6. Various applications, services and sensors used in Agriculture 4.0.

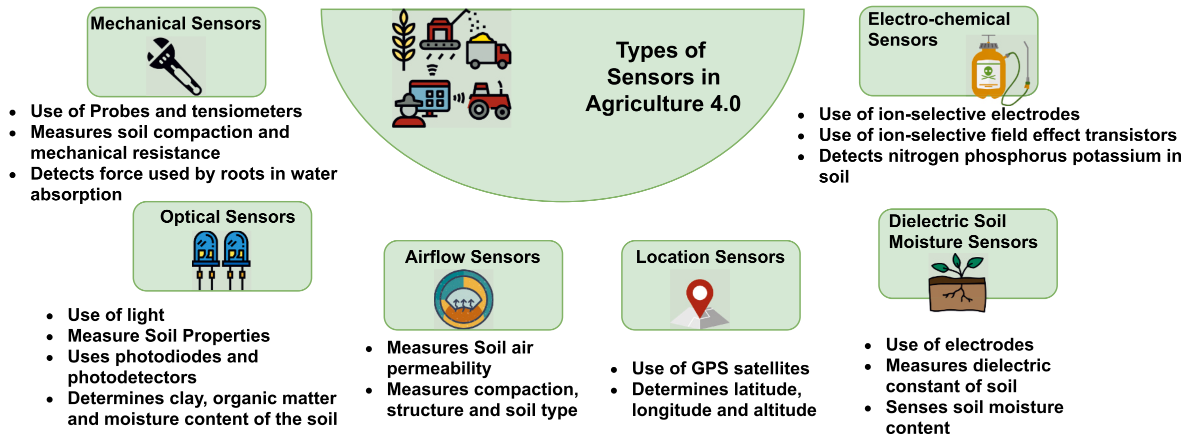

Fig. 7. List of agricultural sensors and their features.

when harvesting. The SW 6010, along with Octinion for strawberries, Sweeper as a robot for peppers, and FFRobot are a few of the foremost robots used for harvesting the crops.

2.3.3. Cloud computing

By enhancing agricultural activities through improved fact-based decision-making, Agriculture 4.0 proves its capability and advantages. Cloud platforms can be used by farmers to obtain information from quantitative analytics organizations such that the best product can be identified as per their requirements. A vast amount of information and expertise relevant to agricultural practices and on equipment available in the market can be accessed by the farmers through the provision of knowledge based repositories provided by these cloud platforms. AgJunction ("Cloud Computing Helps Ag, 2015) has created an open cloud system, which collects and disseminates information from various agricultural control systems, leading to cost reductions and decreased negative impacts on the environment. Furthermore, Fujitsu's proposal for the "Akisai" cloud ("Fujitsu Launches New "Ak) centered on food and agrarian industrial sectors also includes information systems in order to increase food supply in the future.

Many technical leaders are endorsing these advances in view of the IoT's potential use for agriculture applications(Ayaz et al., 2019). Table 2 lists major global organizations, that have proposed IoT-based farming initiatives in agricultural technology (Ayaz et al., 2019).

2.4. Data communication in agriculture 4.0

The backbone of Agriculture 4.0 is the communication and timely reporting of the information. Unless a safe, competent and stable connection between different interacting entities is established, the desired outcomes can never be obtained. Network operators have a significant role in promoting communications efficiency in the agriculture market. In order to incorporate IoT in the agricultural industry on a massive scale, we need to provide an appropriate large framework. Different communication methods and technologies are used to this end, depending on the scalability, availability, and application needs, most common of which are discussed here (Gill, 2021).

2.4.1. Cellular communication

textcolorblueCellular networking modes ranging from 2G to 4G can be used for data communication in Agriculture 4.0 based on the bandwidth requirements. Emerging communication technologies like 5G have enabled networking and data transfer between various devices deployed thorughout the farmland (Kumhar and Bhatia). But the signal strength of cellular networks and their availability in remote areas is a major concern. The preference of a mode of communication often relies on the system specifications. For example some farms may need sensors that can function at a lower rate of data but have to operate for long periods, thus needing long battery life. The new LPWAN system is preferred for mobile networking in these circumstances, not just because of its longer battery life but also because of a wider communication range and cheaper rates.There is a broad variety of short-to medium--range communications in mesh networks apart from WAN (Zulkifli and Noor, 2017).

2.4.2. Zigbee

Zigbee is specifically intended as an alternative to current non-standard devices and technologies for an assortment of applications. The devices working with this protocol are of three different varieties: router, coordinator, and end-user. In addition to this, Star, Mesh, and Cluster Tree (de Oliveira et al., 2017) are the topologies facilitated by the Zigbee networks. Premised on these attributes and taking into account the requirements for agriculture applications, Zigbee may play a major part in targeting the environment in which communications of short distances are necessary. During the monitoring of different variables, the sensor node's time data is transmitted to the end-server via Zigbee. Zigbee devices are configured for networking, e.g. tracking soil contents, such as moisture in the drip irrigation for fertilization and irrigation.

2.4.3. Bluetooth

Bluetooth is a technology for wireless communications, typically links small head appliances over relatively short distances present within close vicinity. The potential benefits of reduced power demands, a quick and easy process and low costs have led to the type of technology being used in several smart agriculture applications. With the introduction of Bluetooth Low Energy (BLE), generally called Bluetooth Smart, Bluetooth has enabled breakthroughs in countless IoT systems. Its innate support for cellphone reachability is the biggest reason for BLE being widely chosen for communication purposes.

2.4.4. LoRa

LoRa communication technology can be described as a long-range, low-energy platform that is commonly used in the IoT industry. It provides LPWAN connection between wifi sensors and the cloud, as its energy consumption is significantly low. It is proven a lot more efficient and secure in restaurants or culinary environments than wifi, bluetooth, etc. Most importantly, LoRa signals can cover a larger network area by penetrating through dense and enclosed entities and also buildings. In general, LoRa-based networks operate longer and also have lowered maintenance expenses (Petäjäjärvi et al., 2017). In (Jedermann et al., (2018)), an analysis with complete coverage, was carried out in a warehouse capable of storing forty tonnes of apples, showing the successful transfer of temperature and airflow observations at a packet rate

Table 2
Current status and future plans of tech companies concerning agriculture 4.0 and PA.

Company	Current Action	Planned Vision
Dell	Joined with AeroFarms (a vertical farming force)	• AeroFarms is more productive and utilizes 95% less water than the traditional farm with the help from Dell's IoT team • Introduced agricultural robots and machines containing most recent AI and ML capabilities
Farm2050	Farm2050	• More than 25 of the world's driving associations are banding together with this association • Proposed to go up against the worldwide challenge of a 70% expansion in food creation to take care of the worldwide populace of 10 billion by 2050 • Basic objective is to use innovation to propel the eventual fate of food by AgTech business visionaries and new businesses
Google	Climate Recipes Plan Joined with MIT Media LabOpen Agriculture Initiative	• Climate Recipes plan recommends arrangements dependent on cross connecting plant phenotypic reactions to natural, organic and other hereditary factors • Aim is to offer healthier food systems • Includes Food Computer gadgets to give the most recent cloud-based administrations in farming
Hello Tractors	Dubbed Digital WalletJoined with IBM Research	• An AI and blockchain-based platform that particularly centers with respect to Africa's farmers (Leduc et al., 2021) • Targets on furnishing small-scale farmers with technological gear and data analytics to make an agriculture practice smart • The cloud-based assistance is expected to help Hello Tractors' business
HPE	Joined with Purdue University	• Blending exploration, developments and advancements such as IoT and distributed computing to change traditional practices in computerized farming • Produce quality food and fuel effectively • University uses a blend of remote sensors and edge figuring innovations given by HPE • Processes tremendous volumes of information utilizing an HPE supercomputer
Intel	Intiswift	• An IoT platform based on superior Intel design • Basic intention is to assist the cultivating business with building associated and information-rich arrangements • The arrangements safely gather, transmit, investigate and follow up on key information • Works intimately with cultivators, makers and specialist co-ops
CISCO	Jasper	• Provides a programming platform in the cloud-based architecture for the IoT in Agribusiness • Helps IoT administrations to benefit from robotization, constant perceivability and remote diagnostics to accomplish smart farming
Microsoft	AI for Earth FarmBeats	• In IAI for Earth program, Microsoft targets four basic territories: atmosphere, horticulture, biodiversity and water • Use their abilities in distributed computing, IoT and AI to tackle farming issues • FarmBeats intended to present exclusive solutions to democratize services like AI among agriculturists throughout the world
Qualcomm	Partners with Ninjacart Partners with Strider Partners with FarmEasy	• Invests in AgTech fire up Prospera that combines data analytics, CV and AI administrations with the aim of helping farmers • Leading remote innovation players throughout the last 15 years
IBM	Watson Decision	• An AI-based service • Helps farmers make better decisions throughout the harvest stages • Provides a platform for agriculture with an aim to give a boost to the harvests, supportability as well as the nature of the smart farming by utilizing modern innovation and IoT

of over 96 percent. Similarly, a method was provided to ensure the quality of food through traceability of data in the grain transit system by controlling the relative humidity and temperature conditions in (Zhu et al., (2018)).

2.4.5. Smartphones

Cellphones are an extremely popular source and a predominant way to communicate if the rural farmers need to be contacted and updated. The continued expansion of mobile networks in developing nations has enabled isolated, dispersed farmers to be reached with enhanced services. IT experts are attracted by the various functionalities, like the camera, the microphone accelerometer, the GPS, and the gyroscope. Hence, they are developing an increased number of mobile applications that take into account the various requirements of the farmers (Alfian et al., 2017; Pongnumkul et al., 2015).

The most relevant aspect of these applications is that farmers ought to access and utilize them. Therefore a simple, free or inexpensive application that incorporates multiple languages and hence, attracts farmers' interest must be developed. Developers and programmers should also research and take numerous factors into account before rendering any suggestion. Market prices, for example, are significant for farmers, but they would not help if roads were bad and the right vehicles were not available. Rather than concentrating solely on farmers, developers should tackle transport, brokerage, and even agricultural experts' problems. Furthermore, in lieu of independent and validated market information, most of the applications have been developed upon grower's presumptions. The developers must concentrate on the data obtained by academic investigators and must also analyze them over different usage periods and conditions. Table 3 provides a few significant mobile applications along with their functions and accomplishments, available for different agricultural applications.

3. Use of unmanned aerial vehicles (UAV) and thermal remote sensing in agriculture 4.0

Remote sensing in Agriculture 4.0 uses satellite, aircraft or ground equipments for the gathering and analysis of data on crop characteristics and soil characteristics. Sensor nodes accumulate energy from various regions of the electromagnetic spectrum, reflected, backscattered, or released across its plane or atmosphere. The types of platforms, the size and number of spectral bands, energy sources, and space resolution, time resolution, and radiometric resolution utilized by sensors in the acquisition of these data affect the applications of remote sensing in Agriculture 4.0 (Kempet al., 2008).

Optical remote sensing is one of the most widely used remote sensing systems in agriculture. It uses near-infrared (NIR) and visible sensors in order to generate images of the surface of the earth by capturing the energy from the plane of the intended location (Prasad et al., 2011). A number of studies (Hatfield and Prueger, 2010; Gitelson et al., 2003; Huete et al., 2002; Jordan, 1969) have investigated vegetative requirements in farming, leveraging NIR and visible images obtained from satellites, conventional aircrafts and UAVs. A mixture of various

Table 3
Noteworthy applications available for smartphone for agricultural applications.

Mobile Applications	Agricultural Application	Features
PocketLAI (Orlando et al., 2016)(2016)	Irrigation	Approximates Leaf Area Index (LAI) Procures pictures 57.5° beneath the canopy using the versatile camera as well as accelerometer sensor
WheatCam (Ceballos et al., 2019)(2019)	Crop Insurance	Inspired by Picture-Based Insurance (PBI)Using the Smartphone camera, pictures of the area of the harmed area before and after the harm are captured
LandPKS (Herrick et al., 2016)(2016)	Soil Assessment	Helps to improve the comprehension of farmers with respect to the land's latent capacitySupports farmers to adapt to environmental change and alleviation exercises
BioLeaf (Machado et al., 2016)(2016)	Health Monitoring	Detects leaf damage, particularly because of bugsMonitors crop foliar status
PETEFA (Palomino et al., 2018)(2018)	Geographic Information System	Provides a geo-referenced soil analysisProvides the Normalized Difference Vegetation Index (NDVI) data of diverse yields at different phases of the lifecycle
WISE (Bartlett et al., 2015)(2015)	Irrigation	Cloud-based irrigation scheduling toolEnables clients to examine their soil moisture scarceness and view climate estimations
AMACA (Sopegno et al., 2016)(2016)	Machinery	User's expectations are connected to the design attributes of the applicationHelpful to assess the expense of apparatus and its usage in different field activities
VillageTree (Suen et al., 2014)(2014)	Pest Management	Offers intelligent solutions to manage pests by collecting incident reports of pests Uses a crowdsourcing methodSends pictures and the GPS data to caution farmers that might be affected
Ecofert (Bueno-Delgado et al., 2016)(2016)	Fertilizer Management	Calculates the best blend of composts dependent on the necessary supplement arrangement and requirements of different yields Takes into account the expense of composts dependent on current market costs
Weedsmart (Scholz, 2018)(2018)	Weed Management	Application evaluates weed seed bank risk and herbicide resistanceEnhances weed management for a specific paddock
eFarm (Yu et al., 2017)(2017)	Geographic Information System	Suitable for detecting, mapping and displaying of farming area framework contemplatesCollects geo-tagged agricultural land information
SWApp (Freebairn et al., 2017)(2017)	Irrigation	Monitors soil water moisture and even considers the climate historyTargets dry land areas explicitly
SnapCard (Ferguson et al., 2016)(2016)	Spraying applications	Uses different sensors of smartphone and measures droplet position by following five imaging methods In-field analysis of spray collectors based on imaging analysis
AgriMaps (Jordan et al., 2016)(2016)	Land Management	Provides a platform to visualise spatial dataFollows a proof-based, site explicit strategy to make proposals for overseeing yield and land

wavebands to quantify different plant parameters, such as the leaf area, biomass, residue cover, chlorophyll content, etc. has led to the development of various vegetation indices (VIs). While the VIs indicate vegetative cover requirements, these response variables are significantly slow as they usually adapt only upon major crop damages. On the other hand, heat sensors detect the surface temperature that acts as a quick response parameter to track plant growth (Stark et al., 2014; Anderson et al., 2013; Hajare et al., 2021).

Drones typically gather information from the visible spectrum of radiation that the ground reflects. For agricultural purposes, various cameras and sensors are used considering the interest of the farmer. Thermal sensors are used to detect the amount of water in plants because leaves with more exposure to water are placed in the blue spectrum of heat map. A similar phenomenon applies in NIR sensors that highlights the differences between the visible and NIR reflectance, such as the Normalized Difference Vegetation Index (NDVI) (Cozzolino et al., 2015). The wavelengths of invisible and visible radiation are captured by the hyper-spectral sensors and cameras, respectively. This captured radiation classifies different plant species and thereby helping to identify undesirable weeds and herbicides (Adão et al., 2017).

3.1. Types of UAVs used in agriculture 4.0 and their applications

In several industries, including the agricultural sectors such as fishing, poultry, farming and others, IoT has made impressive advancements. The rise of IoT in agriculture is however, limited by the scarce networking facilities such as base stations, wifi routers, cellular towers in the proximity of farmlands. With the lack of robust communication infrastructure, data collected from the wireless sensors is not transmitted to the cloud in real-time. In such circumstances, UAVs offer a solution by visiting the wireless sensors and communicating with them across large areas so that the data can be gathered for further interpretation and analysis.

In agriculture, UAVs are usually classified as fixed and multi-rotor drones (Tang and Shao, 2015) (Fig. 8). Even though both, in cost and payload capabilities are available in different ranges, most of them are differentiated through hardware variations. If a wide area needs to be covered, for instance, fixed-wing drones are recommended because they have a long-range flight capability, like the eBee SQ (Best Drones for Agriculture, 2019) by senseFly and DATAhawk ("Questuav- Datahawk Agric). However, multi-rotor drones are preferred because they are simple and fast to configure and their capability to lift off and touch down vertically. Multi-rotors have a lot of benefits compared to fixed wings since these drones are more easier to control, prior wind preparation is not necessary, and they also contain the capability to fly quite accurately. Multi-rotor drones are also viewed as the safer choice in situations where low-altitude flights are desired to acquire highly detailed images. For example, DJI Matrice 200 (PrecisionHawk) and American Robotics' introducing Scout ("ully Autonomous Drone), are regarded as completely automated drones for the daily scouting purposes of the farmers.

At present, agriculture is one of the key fields where UAVs are providing solutions for several predominant and long-term problems. Below are some areas wherein drones play a vital role in supporting farmers during the entire cultivation process.

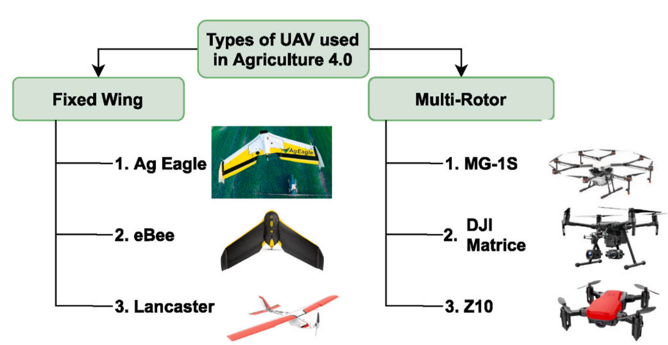

Fig. 8. Popular universal fixed-wing and multi-rotor drones for agriculture.

3.1.1. Analysis of soil and field

Drones can provide detailed soil analysis information before planting, which helps to decide the crop that is most ideal for particular soil conditions and also, indicates the type of seed and the methods of planting to be used. In (D'Oleire-Oltmanns et al., 2012), authors discussed their research findings using a fixed-wing aircraft Sirius I, attached with a Panasonic Lumix GF1 digital camera, to photograph pictures of various locations to monitor the Moroccans' problem of soil erosion.

3.1.2. Planting

Thousands of acres of farmland are underutilised because of inaccessibility to people or the absence of an adequate workforce. To this end, drone-based plantation systems are built, which not only reduce planting costs ("Harvesting the Agricultu, 2017), but can also plant approximately one million trees in a day, saving s significant amount of time ("Drone reforestation. Qui). These plantation systems shoot pods containing seeds and nutrients necessary for the plants to grow. This technique has been proven beneficial, with a rate of success greater than that of 75% for rough terrain ("These Tree-Planting Dron).

3.1.3. Crop monitoring

Crop surveillance is a challenging job as it encompasses vast areas. Drones provide solutions that ensure more reliable and cost-effective monitoring of remote farms in real time. A research was undertaken in (Szewczyk et al., (2018)), wherein the authors were tracking crop conditions with UAVs equipped with digital camera. The main aim of the research was to identify the correlation between the spectral properties of crops and the impact of the availability of fertilizers on plant health. In addition, a groundbreaking method is provided for measuring and mapping the geometrical 3-dimensional characteristics for trees rows in (Torres-Sánchez et al., (2015)). The resulting maps help to explain the association between the growth of trees and the factors related to fields, such as their geometry and resources.

3.1.4. Irrigation

UAVs fitted with various cameras and sensors help determine sites under water stress and identify the necessary, appropriate irrigation modifications. In addition, UAVs also scrutinize the irrigation characteristics and offer solutions through precise water sprinkling only across areas under water stress. The UAVs play a major role in saving water by identifying any irrigation leaks or pooling. AGRASMG-1 ("G-1". https://www) and JT20L-606 ("20L sprinkler drone for) are some examples of drones built specifically to this end.

3.1.5. Spraying the pesticides/herbicides

UAVs could also be used for spraying herbicides or pesticides in crop fields. Pesticides or herbicides are traditionally sprayed throughout the field, which in the majority of cases is not needed. UAVs can explicitly spray on undesirable weeds or treat just the affected areas. Drones can help reduce the total costs, as spraying with drones is highly controlled, and the drone will spray only when it is absolutely necessary. Management of unexpected changes in the climate, such as wind speed and direction, is especially a problem for UAVs when used in spray applications. To this end, a computer-based program is proposed in (Faiçal et al., (2017)) that efficiently follows the control rules of UAVs in order to ensure correct manoeuvring of the pesticides.

3.1.6. Health assessment

Infrared (IR) and visible light sensors on drones can be used to recognize plants that are contaminated by fungus or bacteria on a daily basis. For these problems, early identification effectively prevents the disease outbreaks to other crop areas or plants. In (Puig et al., (2015), UAVs are used for terrestrial sensors data collection, which includes a chlorophyll meter as well as a spectroradiometer. This data collected then helps in determining plant health and quality.

Recent developments in swarm technologies and controlled missions allow groups of drones fitted with diverse sensor systems and 3-dimensional cameras to operate collectively and furnish the farmers with extensive land management skills and abilities. However, several obstacles must be overcome to gain from the potential advantages of this strategy, particularly the convergence with other technologies and identifying some method to use UAVs in dire weather conditions (Chamola et al., 2020). Throughout the world, there are hundreds of drone manufacturers or operators, about a third of which provide valuable services to farmers. Table 4 lists drone manufacturing companies, data science, and service providers in agriculture (Best Drones For Agriculture, 2020).

3.2. Applications of thermal remote sensing in agriculture 4.0

Thermal Remote Sensing is a method of radiation measurement, emitted from the surface of an entity that is transformed into temperature devoid of any immediate contact with the entity. Radiation is emitted from all artifacts having a temperature above 0 K or −273 °C or −459 °F. This radiation is dependent on the surface reflectivity and temperature of the surface of the artefact (Prakash, 2000). Thermal remote sensing offers valuable readings for energy flows and surface temperatures, that are essential to topographical methodologies and feedback (Quattrochi and Luvall, 1999; Weng, 2009). Thermal remote sensing can be widely employed in several areas of agricultural soil and yield monitoring, such as crop and soil moisture stress assessment in order to schedule irrigation, crop disease identification, soil composition mapping, residue cover estimates, field tile location, crop maturity and yield monitoring. This section briefly describes the various studies that have been carried out to establish possible uses of thermal images in agricultural sector. Table 5 gives a summary of a few of these studies of thermal imaging applications in agriculture.

3.2.1. Irrigation scheduling

For areas where in-season precipitation is insufficient to fulfill the demands of water for crops, irrigation is an essential component of agricultural development. Understanding the location and its required amount of irrigation minimizes loss of water-related crop yield, maximizes return on other management activities, and optimizes yield per application water unit. The irrigation requirements primarily depends on four factors – water quantity and quality in soil, need for crop water, rainfall, and irrigation system performance (Rhoads and Yonts, 1991). Researchers have analyzed the potential to use thermal images from different platforms such as aerial, satellites and UAVs as methods to quantify such variables (Shafian and Maas, 2015; Hillel, 2013; Soliman et al., 2013; Chávez et al., 2008; Carlson, 2007), and illustrate that timely delivery of these data may improve irrigation schedule frequency and timing during the critical crop phenologies.

3.2.2. Plant disease detection

Thermal remote sensing studies have shown that the spatio-temporal trends of crop diseases can be assessed before any signs of symptoms and can also be tracked at different stages of disease advancement. Impairments because of root pathogens, or foliar pathogens, like rusts or leaf spots, usually affect the rate of transpiration of the plants or plant organs (Mahlein, 2016). A demonstration of fluctuations in temperature levels was recorded in the early stages of growth of sugar beet due to leaf spot ailments prior to any real damage in (Chaerle et al., (2004)). In addition, the studies in (Mahlein et al., (2012); Stoll et al., (2008)), suggest that thermal sensors are far more suitable than optical, multi-spectral and hyperspectral sensors to identify disease-induced premature alterations of plant respiration and water and leaf temperatures.

3.2.3. Soil texture mapping

The surface temperature of the land is strongly associated with the structure of the soil. The soil texture affects the moisture content of the

Table 4
List of drone manufacturing companies, data science and service providers in agriculture.

Organisation	Product and Service Offered	Country
Drones and Sensors in Agriculture	These manufacturers produce the world's most popular UAVs and sensors for smart agriculture.	
1. Skycision	Solution to identify and analyze crop stresses using drones.	United States
2. AgEagle	Drones for agricultural data capture.	United States
3. Sentera	Drones, software applications and sensors for agriculture.	United States
4. American Robotics	Developer of specialized drones for automation in agriculture.	United States
5. Sensefly (Parrot)	Geospatial data collection and analysis drones, including an aerial analysis system for crops.	Switzerland
6. DJI	Flying platforms, sensor packages and aerial crop monitoring software.	Hong Kong
7. Skycision	Solution to identify and analyze agricultural operations and crop stresses using drones.	United States
Aerial Imaging and Analytics	**These image manufacturers use their own equipment and supply sensor and camera data, charging by the acre.**	
1. TellusLabs (Indigo Ag)	Combines historical satellite imaging and computer mapping and agricultural supply chain prediction.	United States
2. AGERpoint	Capture accurate farming data with the drones enabled by LiDAR.	United States
3. Hummingbird	Artificial Intelligence company that provides farmers with advanced crop analysis.	UK
4. Aerobotics	Early pest and satellite imagery-led disease detection solution.	South Africa
5. Gamaya	A method of agricultural management using hyperspectral imaging and data processing.	Switzerland
6. Astro Digital	Company of global research and imaging satellites. Nano-satellites are used to capture visible and infrared images.	United States
7. Farm Shots (Syngenta)	The analysis of satellite and drone imagery identifies pathogens, pests and low plant nutrition on farms.	United States
Presticide Spraying	**These UAV manufacturers supply drones for carrying and spraying pesticides and other fluids.**	
1. Rantizo	A simple-to-use drone spraying system that outputs accurately where needed and when necessary.	United States
2. Airboard Agro	First farming drone for industrial pesticide and fertilizer pumping with a capacity of 100 L.	United States
3. Skyx	Drones for spraying crops.	Canada
4. DJI	DJI Agras Agricultural Drones series is a popular8-rotor multicopter for spraying pesticides and liquids.	Hong Kong
5. HSE	11 UAV crop duster agricultural versions, 6 helicopters and 5 UAV crop dusters.	United States
Smart Farm Technology	***Any of these programs or utilities may be used to operate the users' own UAV fleet and data to control the farm.***	
1. Slantrange	Slantrange uses specialist sensing equipment, drones and analytical instruments for informing farmers about crop safety.	United States
2. Cainthus	Uses machine vision equipment to track crop and animal safety and welfare.	United States
3. Resson	Farm analytics approach uses drones, machine learning and in-ground sensor data to generate observations.	United States
4. FluroSat	Uses satellites and drone imagery for disease prediction and help farmers take decisions.	Australia

soil, which impacts the temperature of the land surface (Mattikalli et al., 1998). For instance, soil with a sandy texture having low water retention capacity is projected to possess an accelerated rate of water depletion and a relatively poor soil moisture content during dry seasons, resulting in increased surface temperature. On the other hand, a clay soil having greater water retention capacity demonstrates a lower erosion pace and increased soil moisture content which results in a decreased temperature of the land surface (Wang et al., 2015). Studies have shown the usage of thermal remote sensing in order to determine the texture of land on a large scale by analyzing the variations in textcolorbluetemperature of the soil surface in a comparable environment.

3.2.4. *Residue cover and tillage mapping*

The soil and water preservation is made possible by crop residues which develop a defensive layer throughout the agricultural fields that protects the soil against degradation from water and wind, decreases humidity deprivation and heightens the consistency of the soil. For close control and enforcement of conservation tillage activities, an objective evaluation of the extent of cultivated residues is necessary (Hively, 2015). Studies in (Kozak et al., (2007)) and (Potter et al., 1985) show the ability of thermal images for mapping residue coverage by comparing the deviations in the surface temperature of soil between traditional and no-till systems. The analysis in (Sullivan et al., (2004)) showed that the thermal images could describe ninety-five percent of crop residue component, compared to that of seventy-seven percent by near IR and visible images.

3.2.5. *Field tile mapping*

Tile drainage systems extract the excessive water from the farmlands, resulting in environmental and economic gains (Hofstrand, 2010). At the same time though, there may be large amounts of nutrients such as nitrogen and phosphorous in tile water that may lead to low water quality (King et al., 2015; Smith et al., 2015). By enabling the farmers and environmental resource planners to monitor areas of tile drains will allow them to properly anticipate and reduce negative economic and environmental effects in such regions. Studies in (Naz et al., (2009); Naz and Bowling, (2008)) have demonstrated that the visible images and the NIR images can be used in confined areas for the identification of tile positions. As the soil dries more rapidly in tiledrained fields, the temperatures of tile-drained and naturally drained fields may differ (Yanru and Xiaohong, 1998). Thermal images can furnish new possibilities of tile mapping in fields by analyzing temperature variations in a field (Hoffman and Erb, 2016).

3.2.6. *Crop maturity mapping*

In order to assess the ability of a crop to adapt to presumably seasons of lower precipitation such as drought, an early evaluation of crop maturity is important (Jensen et al., 2009). The respiration and transpiration of crops is affected by their physiological state and type, which impacts their thermal conditions. The degree of respiratory intensity declines of many crops at maturity when compared with the initial phase of development (Linke et al., 2000). In fact, reduced respiration contributes to increased temperatures. Fruit load plays a significant role for fruit trees in regulating respiration and transpiration. The temperatures of the canopy of trees with zero fruit load are higher in relation to the trees having fruit load.

3.2.7. *Crop yield mapping*

For farmers, an early and precise estimation of the agricultural productivity is beneficial for several purposes, namely crop insurance, field harvesting and storage needs and budgeting for cash flows. A large number of studies were undertaken to predict crop productivity using satellite and airborne sensor images at regional levels (Sakamoto et al., 2013; Mkhabela et al., 2011) and field levels (Geipel et al., 2014). The expected production and the total bio-mass of the rice crops in Thailand (Swain et al., 2010) and prediction of corn yields in Germany in the midseason (Geipel et al., 2014), were extracted from the images obtained by UAVs. However, these experiments have concentrated on visible and NIR obtained images of VIs.

Table 5
Thermal imaging applications at different geographical scales in agriculture.

Area in Agriculture	Challenge	Observations	GeographicScale	Platform
Water stress of crop	• Variance in temperature of canopy for water pressure identification	• Suited for precise water sources management	OrchardRegional	Ground Aerial Satellite
Maturity mapping of crop	• Features of produce, eg. foods grown from the ground at pre-and-post gather phases are obscure	• Determining microbial invasion and newness status of produce • Thermal images can be used to analyze conditions for pre-harvest • Assessment of environment for post-harvest	Laboratory	Ground
Mapping of crop yield	• Fruit recognition is difficult • Harvesting the crops of speciality manually is costly • Need for a simple technique for checking quality of products and estimating their yield	• Aids in establishing robotic fruit gathering • Possible to anticipate the yield of fruit	Orchard	Ground
Evapo- Transpiration (ET) and drought Stress	• Need for a quick analytic reaction indicator portraying ET deficiencies • Improve trust in signs of emerging dry spell	• Provide early alerts for drought conditions • Estimates of ET based on RS is as competitive as with ET noted at field level	Field Regional National	Aerial Satellite
Detection of plant disease	• Early identification of pathogens lead to improved efficiency of pesticide application	• Advancement of pathogens can be discovered at an early period with the use of thermal images	Orchard Greenhouse	Aerial Ground
Residue cover and tillage mapping	• Measure the residue consequences of residue on the temperature of soil and water • Existing techniques that quantify residues of crop are difficult, and generally seem inappropriate to field-scale the provincial estimates	• Plots with more quantity of residue spread results in reduced temperature of surface • Thermal pictures can be utilized to evaluate crop residue inconsistency	Regional	Airborne
Soil moisture	• Mapping of the soil moisture spatial allocation and screening the change in its status after some intervals	• Thermal pictures can be utilized for observing the soil moisture status at the territorial scales • Air-borne thermal images of coarse resolution performed superior to a handheld thermal firearm	Fields Vineyards Regional	Ground Aerial Satellite

4. Internet of underground things in agriculture 4.0

Recently, a new IoT category has emerged because of the necessity for in situ real-time knowledge from farmlands: Internet Of Underground Things (IoUT). IoUT embodies independent equipment that gathers data pertaining to our planet and is intertwined with networking and communication solutions that enable information to be sent to farmers and decision-makers from different fields. In IoUT, communications from underground devices can be channelled through plants and soil and the knowledge gleaned from the fields can be submitted to the cloud in order to make real-time decisions.

IoUT implementations have specific requirements: the ground knowledge, remote crop field activities, wireless plant and soil communications, and accessibility to various elements. There are major problems challenging the existing wireless over-the-air (OTA) networking technologies, since they had not been built to account for such scenarios. IoUT has led to wireless underground (UG) transmissions (Akyildiz and Stuntebeck, 2006; Vuran and Akyildiz, 2010) that reaches radios submerged in the ground and wireless transmission takes place partly or entirely through the earth. IoUT can aim to preserve water sources and enhance crop productivity through UG communications. Large initiatives such as the tracking of the landslides, pipeline inspection, underground mining activities and border enforcement can benefit from the advancements accomplished by IoUT. We provide an overview of the technologies that allow IoUT to address specific challenges related to system and communication. We categorize such systems into two categories IoUT Testbeds and Industrial IoUT systems (Vuran et al., 2018).

4.1. Academic IoUT systems

IoUTs can be made to work with irrigation control systems to measure the quantity of water and fertilizers that needs to be applied. The South Central Agricultural Laboratory (SCAL) located in Clay Center, Nebraska has deployed an IoUT testbed (Dong et al., 2013). This testbed encompasses a 41-acres area for research. In 2005, an innovative central pivot irrigation control system was built in the testbed to investigate the long-term dynamics of varying irrigation rates, water for crops and nutrients absorption, and the relationship between water constraints and crop yields (Irmak, 2015). It studied the crop growth functions and related topics in marginal and relatively low irrigation and precipitation environment. A portable sink is set upon one of the irrigation system's control towers (Dong et al., 2013). About, ten to sixteen Underground Things (UTs) are deeply distributed around the field. Each UT is able to establish the temperature of the soil and determine moisture from 4 external sensors embedded at a distance of 1 ft range from each other. UTs have a lithium-ion battery and are covered with a waterproof shell. The data received real-time from a UT is merged in a portable sink and transmitted through 4 G connectivity to the cloud. The cloud interacts with the central pivot control panel to control irrigation in an automated way. This testbed is a complete integrated system built for the analysis of IoUT communication and sensing in an agricultural area with central pivot irrigation, sensors, and communication equipment present above the ground and underground.

SoilBED (Farid et al., 2006), is an underground testbed designed for soil-based experiments of cross-well radar. It is used to scrutinize the spread of EM waves and to identify the presence of irradiated soil materials. SoilBED is also be used to define the subterranean channel and antenna and to validate the underground channel communication models empirically. Thoreau (Zhang et al., 2017) is an on-campus IoUT testbed, where time and geo-tagged data are collected and curated in an open cloud-based platform. It is built on Sigfox and works with a high frequency and a narrowband function in the unlicensed bands of 900 MHz. It has extremely reduced data speeds and it measures characteristics of the soil, along with its moisture, temperature, and electrical conductivity.

Internet of Food and Farm (IoF2020) (Iof 2020 and https://www.iof2, 2020) has 19 applications in 5 fields of the agri-food industry: arable, vegetables, fruits, dairy and meat processing. One instance in arable is the integration of sensor network data for smart wheat handling, crop simulation and other sources of data, such as, disease identification, crop stage detection, phenotyping characterizations, etc. in order to achieve an increased spatial-temporal precision and to create innovative models. An example of case study in vegetables consists of monitoring the tomato-crop chain in greenhouse by creating optimal ecosystem conditions to minimize resource use and improve energy usage. In the dairy, grazing cows are monitored with three beacons on the pasture and in the dairy barn. For instance, RFID tags can track swine meat to reduce boar imprints and improve health productivity. Monitoring climate, logging weight gain, drinking and eating habits, and their intake of water and food are also registered by the sensors.

In (Ye et al., (2016)), an IoUT system based on ZigBee with the purpose of being used in PA was developed. This architecture is used for monitoring associated soil characteristics, such as, its pH levels and humidity. In Sierra Nevada, California, an IoUT testbed was developed for measuring the moisture levels of snow and soil (Kerkez et al., 2012). This type of IoUT sensor testbed is made to log the measured water content in the soil, the depth of snow, and some more relevant attributes, with the help of 300 sensors spread over a range of few kilometres. It also provides comprehensive sensing and communication efficiency reports. Table 6 provides a synopsis of the prevalent academic architectures (Vuran et al., 2018).

4.2. Industrial IoUT solutions

Almost all commodities use wireless OTA connections, wherein UTs are equipped with various premium sensors which measure the moisture content of the soil, electrical conductivity, and temperature. UTs can connect to establish an interaction mesh but, in certain scenarios, these UTs are directly linked to a field tower with the abilities for satellite or cellular communication. Modularity is highly important when developing IoUT systems, provided that specifications can differ with time and are adapted for a particular task. In certain instances, it is important to use original equipment manufacturer (OEM) components for the design of more accurate and fast prototyping. Once processed, end-users require data transfer networks, storage and computing facilities, and cloud-based software to visualise the data. There are organizations specializing in solutions for agriculture. Table 7 outlines the Industrial IoUT solutions for PA and the following are the main classes of these industrial solutions (Vuran et al., 2018).

4.2.1. Agricultural solutions

Field Connect by John Deere utilizes a 3G network for the transmission of data from probes consisting of eight sensors and placed at a distance of one mile, measuring soil moisture at different depths, temperature, wind direction and speed, amount of rainfall, and wetness of leaf. MimosaTEK offers farms with fertilization and irrigation technologies (“MimosaK – Elevating tr). Wireless solutions for humidity and temperature control in grain elevators are provided by TempuTech (“TempuTech: Technology d). FarmBeats, an artificial intelligence and IoT platform for agriculture, is being developed by Microsoft (Vasisht et al., 2017). These agricultural solutions support Agriculture 4.0 completely by providing sensing, cloud, and communication services.

4.2.2. Out-of-the-box packages

Smartrek Technologies designs nodes that are wireless which can be effortlessly integrated in a network mesh for various kinds of gateways and sensors (“Smartrek - and S). Nodes are shielded by weather-resistant enclosures, which is a prerequisite for outdoor farming. A Plug & Sense Smart Agriculture solution (“Libelium » Connecting se) developed by Libelium, provides solutions for humidity and temperature sensing, wind direction and speed, rainfall, air pressure, the water content in soil, and the wetness of leaves. Cropx’s (“Cropx Technologies:Welco) IoUT is mainly composed of software and hardware elements used for measuring soil humidity, temperature, and electrical conductivity in order to support decision-making for irrigation in real-time. PrecisionHawk has built an IoUT platform (Precisionkawks) that uses drones to sense and produce field maps. It facilitates thermal, visual, and multi-spectral imagery to generate field maps in PA. These out-of-the-box packages are essential components of the PA to sustain various applications.

4.2.3. OEM components

OEM components generally help large-scale node production.

Table 6
Academic IoUT systems.

Architecture	Sensors	Communication Technology	Node Density
Automated Irrigation System (Gutiérrez et al., 2013)	VH400 (soil moisture)DS1822 (temperature)	ZigBee (ISM) Over-the-air	One node per indoor bed
Autonomous PA (Dong et al., 2013)	Data logger Watermark 200SS-15 (soil moisture)	Custom (ISM) Underground	Up to 20 nodes per field
Cornell’s Digital Agriculture (“Digital Agriculture — Co)	Vineyard mapping technologyE-SynchReal-time KinematicsTouch-sensitive soft robots	Over-the-air	Field Dependant
FarmBeats (Vasisht et al., 2017)	Orthomosaic and pHSoil moistureTemperature	Over-the-air	Field size of 100 acres
MOLES (Tan et al., 2015)	Magnetic Induction Communications	Magnetic Induction	Indoor testbed
Plant Water Status Network (Rojo et al., 2016)	Crop water stress index (CWSI)Modified water stress index (MCWSI)	Over-the-air	Two management zone - Two treatments in each zone
Pervasive Wireless Sensor Network (Wark et al., 2007)	CameraMoisture content of Soil	Over-the-air	Dependant on field
Pilot Sensor Network (Langendoen et al., 2006)	Sensirion SHT75	Over-the-air	Field containing 100 nodes
Purdue University’s Digital Agriculture Initiative (Purdue University’s Digit)	PhenoRover sensor vehicleAdaptive weather tower	Over-the-air	Field Dependant
Real-Time Leaf Temperature Monitor System (Leaf monitor system)	Relative humidityAmbient temperatureLeaf temperature IncidentSolar radiation	Over-the-air	Soil and plant water status monitors
Remote Sensing and Irrigation System (Kim et al., 2008)	CR10 data logger CS616 (soil moisture)TMP107 (temperature)	Bluetooth (ISM)Over-the-air	One weather station sensing five fields
Sensor Network for Irrigation Scheduling (Sensor network for irriga)	Watermark soil moisture sensorsCapacitance (soil moisture)	Over-the-air	6 nodes per acre
SoilBED (Farid et al., 2006)	Contamination detection	Underground	Cross-Well Radar
SoilNet (Bogena et al., 2010)	EC20 TE (soil conductivity)ECHO TE (soil moisture)	ZigBee (ISM)Over-the-air	150 nodes covering 27 ha
Soil Scout (Tiusanen, 2013)	EC-5 (soil moisture)TMP122 (temperature)	Custom (ISM) Underground	Eleven scouts on field and a control node
Thoreau (Zhang et al., 2017)	Water potentialTemperatureElectric conductivitySoil moisture	Over-the-air	Based on Sigfox
Video-surveillance and Data-monitoring WUSN (Garcia-Sanchez et al., 2011)	Camera sensorMotion detectionAgriculture data monitoring	Over-the-air	In the order of several kilometers

Table 7
Industrial IoUT systems.

Architecture	Sensors	Communication Technology	Density of Node
365FarmNet ("Digitalise your farming)	Mobile device visualization tool for IoUT data	Over-the-air	Dependant on Field
Automated Irrigation Advisor ("Tule - Goodbye and Pressure)	Tule actual ET sensor	Over-the-air	Dependant on Field
Cropx Soil Monitoring System ("Cropx Technologies:Welco)	Electrical conductivity Soil temperatureSoil moisture	Over-the-air	Dependant on Field
EZ-Farm ("Case Studies Corporate L)	Satellite information Soil sensorsWater usageWeather Genetics	Over-the-air	Dependant on Field
Field Connect ("John Deere—Products)	Leaf wetnessRain gauge weather stationTemperature probe pyranometer	SatelliteProprietary over-the-airOver-the-airCellular over-the-air	Up to eight nodes per gateway
Grain Monitor-TempuTech ("TempuTech: Technology d)	HumidityGrain temperature	Over-the-air	Multiple Depths in Grain Elevator
HereLab ("HereLab: Drip line psi)	Drip line psi and rainSoil moisture	Over-the-air	Dependant on Field
IRROmesh ("Irrometer Reading Tools.)	Watermark 200SS-15 (soil moisture)200 TS (temperature)	CellularCustom (ISM) over-the-airOver-the-air	Up to 20 nodes network mesh
Internet of Agriculture -BioSense ("Internet of Agriculture, 1256)	Nano and micro-electronic sensors Electrical conductivity mapRemote sensingYield mapNDVI mapMachinery auto-steering and automation EC probe & XRF scanner	Over-the-air	Dependant on Field - Irrigation decision making in real-time
Internet of Food and Farm (Iof 2020 and https://www.iof2, 2020)	Leaf wetnessElectrical conductivitySoil temperatureSoil moisture	Over-the-air	Dependant on Field
IntelliFarms (AGI SureTrack IntelliFarms biological BinManager)	Biological BinManagerYieldFax	Over-the-air	Dependant on Field
IoT Sensor Platform ("Smart Ag Products - Zens)	IoT/M2M sensors	Over-the-air	Dependant on Field
Plug & Sense Smart Agriculture ("Libelium » Connecting se)	Leaf wetness Humidity and temperature sensingSoil water contentRainfall Atmospheric pressureVelocity of wind and its direction	Over-the-air	Dependant on Field
PrecisionHawk ("Precisionkawks:Agricultu)	Field map generationDrones for sensing	Over-the-air	Dependant on Field
SapIP Wireless Mesh Network ("Sap-nfrared Leaf)	Plant water useWeather and ET Soil moisture profileMeasure plant stress	Over-the-air	Up to 25 SapIP nodes with 2 sap flow sensors each
SeNet ("Senet: Cloud-Based Softw)	Sensing and control architecture	Over-the-air	Dependant on Field
Symphony Link ("Symphony Link - Internet)	Long Range Communications	Over-the-air	Dependant on Field

However, the procurement of OEM devices is often dependent on the prototyping or development of a particular UT on a limited scale. Semtech Corporation is a provider of sophisticated algorithms and highly efficient semiconductors ("Analog and Mixed-Signal). Telit is an IoT-focused M2M solution company("Telit: Ioolutions Pro). Telit supplies tailor-made software and hardware technologies in small components. Cell, Bluetooth, LoRa, Low Power Wide Area (LPWA), SigFox, and Wifi technologies can be used to send data by the products. Herelab makes the claim that customized IoT platforms can be deployed and prototyped rapidly ("HereLab: Drip line psi). Herelab also conducts workshops and labs to deliver innovative tools and to endorse the use of IoT devices. These elements act as valuable sensing and connectivity blocks for IoUT.

4.2.4. *Cloud-based services*

Users having no prior knowledge of web programming can access worldwide data collected from IoUT devices through cloud services. Farmers, as well as other experts, need not spend time employing some other team to set up a server to utilize the gathered information. They will be able to make the decisions instantly. LORIoT delivers the services of cloud with a low latency, globally dispersed grid of servers that link end-users through their LoRaWan gateways. The services of the web offered include device management, data cloud storage, encryption key safeguard and translation to IP/IPv6 from LoRaWan ("- The LoRaN® Ne). Device Lynk provides a data analysis interface for data obtained by industrial IoT systems ("Devicelynk: Industrial S). IntelliFarms offers various agricultural solutions, namely, crop market pricing, weather reporting, and managing storage conditions in silos and containers. The IntelliFarms platform provides customers with a centralized access to all solutions (AGI SureTrack IntelliFarms biological BinManager).

4.3. *Major challenges for IoUT*

The recent developments in IoUT have extended the range of this field for research. However, there are few challenges faced by the IOUT systems, as discussed below:

4.3.1. *Deployment*

Deploying smart products for IoUT is a daunting challenge in the rugged underground environment (Kisseleff et al., 2018). Contrary to the terrestrial network, the configuration and control of smart underground objects are far more complicated. In fact, during the excavation process, the underground objects can be damaged easily. In order to reduce IoUT integration costs, the effective implementation of smart objects is therefore necessary. For instance, a smart, high-energy requiring device should be positioned closer to the surface for facilitating maintenance, as changing batteries in an underground setting is challenging. In addition, batteries with large capacity and protocols for preserving power could be used to prevent replenishment of batteries.

4.3.2. *Scalability*

Increasing the scalability of the IoUT system may result in an increase in routing operation costs, failure of nodes, and network density. Also, the high consumption of energy and low storage capacity of the underground sensors places a restriction on the scalability of the system. In (Tooker and Vuran, (2012)), the authors explored the question of scalability and maximization of life for farm IoUTs, which used a mobile sink node to link the distributed nodes. A large-scale IoUT was recently introduced in (Zhang et al., (2017)), and a single-hop star topology was implemented that could accommodate up to a million objects. In addition to some of the aforementioned solutions, IoUT also needs self-healing and organizing technology to mitigate the problem of scalability.

4.3.3. Hybrid sensing

A hybrid IoUT sensing system incorporates signals from a number of different sensor systems for event prediction and localization. For instance, for the identification and position of an underground event, a network of underground fiber sensors can be coupled with ground perforating radars. SoilNet system model presented in (Bogena et al., (2010)) is yet another hybrid sensing network. In SoilNet, a ZigBee network based on electromagnetic (EM) waves is used to communicate above the ground and wired connectivity is used to link the underground nodes. The hybrid EM and magnetic induction (MI) based sensing network can also be used in which the EM offers downlink connectivity over a long range while the short-range MI is used to connect with uplinks from multihop (Lin et al., 2017b). Hybrid sensing and new designs like crowd-sensing are therefore capable of proactively detecting and locating underground occurrences and improving IoUT effectiveness.

4.3.4. Big data

IoUT can produce a broad variety of test data across a number of applications, such as forestry, geological surveys, agriculture and oil or gas fields. Therefore, to make a correct analysis, an event correlation, or a metric extrapolation, this humongous amount of data must be organized (Hajirahimova, 2015). For example, a massive amount of exploration data that is generated in the IoUT oil and gas networks, is challenging to manage by the petroleum and gas sector. In (Mohammadpoor and Torabi, (2018)), geoscientists are stated to have spent half their tenure in the management and analysis of the data. This mammoth amount of data can be managed by big data, and different analyses such as, planning and drilling can be carried out. Therefore, in order to manage the enormous quantity of data that are generated in IoUT, proper analytical data tools should be created.

5. Big data in agriculture 4.0

As smart devices and sensors grow in quantities in farms, resulting in an increase in volumes of generated data, agricultural processes are becoming extremely data-driven and data-enabled. Since its inception in the 1980s, PA has redefined agricultural activities by integrating GPS, Geographic Information System (GIS), and remote sensing technologies (Zhang et al., 2002). Over the past few decades, PA has advanced from strategic surveillance for making regional-specific decisions through satellite imagery to operational tracking using the low altitude, remote sensed data for field-specific diagnosis. Today, data science is being integrated into precise farming strategies so that data can be processed quickly for real-time decision-making (Bendre et al., 2015; Wolfert et al., 2017a). However, research is still required into how big data can be manipulated and transformed into small data for particular issues or areas of precise farming operations.

Large-scale data mining has become increasingly popular recently. We can extract and analyze data to get precise results immediately through advancements in computing power, the accessibility of affordable cloud storage, and log information. As early as 1999, researchers had launched a data analytics campaign on a massive scale in agriculture to meet the increasing demand for agricultural production. In (Basso et al., (2001)), a spatial visualization of agricultural grounds was recommended using state-of-the-art technologies like GPS and remote sensing. Since no two businesses are alike, so localized intelligence, which offers site-specific solutions to farmers, has now become extremely important. At first, data collection and curation became a concern for researchers as they were operating with limited data sets. There have, however, been continuous concerns over the future of global food security since 2000. The application of big data resources can overcome these issues.

Data-driven agriculture entails gathering, storage, and analysis of large, diverse, complicated, and spatial data (Yan-e, 2011). The intricacy of the data can vary in text, photos, sound, and video that can be either of structured data type or non-structured data type (Wolfert et al., 2017b). The data may include historical data, sensor data, live streaming data, industrial data, and data from the marketing sector. Using cloud IoT systems, it is possible to store big data from the sensors in the cloud. This also encompasses hosting applications that are essential for the provision of services and the management of the IoT architecture from one end to another. Edge or fog computing has been recently promoted, with gateways and IoT devices performing computation and research to minimize latency, costs and boost QoS (Chen et al., 2018) for essential applications. Many information systems have been designed for agriculture management to maintain different kinds of data (Yan-e, 2011). For example, Onfarm systems, Farmx Farmobile, KAA, Cropx, Easyfarm, and Farmlogs are some of the available commercial platforms. These platforms support data analytics, data management, and data storage operations. Table 8 provides a brief description of various IoT solutions that are available for agriculture.

5.1. Conceptual framework for network management

The regularly referred conceptual framework of (Lambert, (2000)), on how to supervise the network, contains three strongly interrelated components. The first component is the network structure that comprises different organizations and its connections between these organizations. The next component, business processes, are the exercises that generate yields of significant worth to the client. Lastly, the management components consist of the administrative factors which help coordinate the business processes and are overseen by the network. This management component of the network is additionally partitioned as an organization and a technology component. This whole network is customized as needed for the networks in the applications of smart farming using big data (Wolfert et al., 2017b).

The business processes (lower layer) in this framework emphasize Big Data's creation and usage in the management of the agricultural process. This component was therefore segmented into data chain, management of the farm, and agricultural processes. The data chain engages in different decision-making processes by interacting with farming and farm management processes, wherein information happens to play a vital role. The network of stakeholders (middle layer) consists of not only big data users but also corporations specializing in data regulatory and policy management. At last, the network management layer characterizes network technological and organizational structures, which enables the monitoring and integration of the operations carried out by the stakeholder network layer parties. Network management's (upper layer) technology component concentrates on the data chain

Table 8
Platforms for storing, managing, and analysing data in precision agriculture.

Platform	Features
OnFarm	Farm Management tool, Displays and analyses data from multiple sources, Three levels of subscription-free, standard, and enterprise
Phytech	Provides Plant IoT platform, For direct sensing, data analytics and plant status, Provides farmers with decision support service to increase yield and optimize irrigation
Semios	Real-time monitoring service, Event notifications are provided, Focuses on network coverage, pests, frost, diseases, and irrigation for orchards
EZFarm	An IBM project Focuses on Water Management, monitoring of soil, and health of the plant
KAA	An open IoT cloud Platform, Provides remote crop monitoring and resource mapping Provides stats on livestock feeding and produce smart logistics and data warehousing
MbeguChoice	Targeted towards Kenya farmers Helps farmers to access better seeds from various suppliers
FarmLogs	Farm management software, Automatic activity recording and crop health imagery, Three levels of subscription-free, essentials, premium
Cropx	Provides adaptive irrigation software services, Allows to monitor soil anywhere and anytime Delivers crop yield increase, water, and energy cost saving

information infrastructure. The organizational component concentrates on the data chain management and business model. Finally, multiple variables could be established, and challenges could be derived when main drivers increase the implementation in smart farming using big data. The following subsections give a more comprehensive depiction of every component of the layers of network management and business processes of the conceptual framework.

5.2. Farm processes

Big data from the agricultural sector are recognized to be highly heterogeneous in nature (Ishiiet al., 2014). The heterogeneity relates to the field of the data gathered, that is, what is the information about and the methods by which the data is produced. Data gathered from the farms encompasses information for planting, materials, spraying, yields, climate, soil types, etc. There are by and large three classes of generated data (Devlin, 2012): (a) process-mediated (PM), (b) machine-generated (MG) and (c) human-sourced (HS).

The data from ordinary business, known as the PM data, follow the agricultural systems which document and keep track of required business occasions, for instance, buying inputs, fertilization, seeds, etc. PM data are extraordinarily sorted out and consolidate exchanges, reference tables, and their connections, and furthermore the metadata that portrays their specific situation. Data from traditional businesses are mostly the data that IT supervises and take care of in both business and operational data systems, which are by and large sorted out and set aside in database structures.

Data of the type MG are gathered from a number of sensors that are increasing continuously and the savvy machines used for quantifying and recording cultivating processes. MG data go from basic sensor records to complicated PC logs and are commonly well organized. The capability of UAVs has been perceived all around for smart farming (Faulkner et al., 2014). IR cameras and GPS technology-equipped drones are changing modern farming culture with their help in improved management of risks and decision-making. In cultivating domesticated animals, smart dairy ranches are supplanting work with robots in exercises like taking care of cows, cleaning the stables, and milking the cows (Grobart, 2012). With new advances like these, information is not only present in traditional tables, they can furthermore show up in various formats, like audio or images (Sonka, 2015).

HM data is the documentation of human encounters that were earlier documented in arts and books and thereafter in the form of pictures, videos, and audios. Human-sourced data is currently primarily digitized and saved in PCs and social networks. HM data are typically poorly organized and are at times unregulated. With regards to smart farming using big data and, human-sourced information has only been considered from the perspective of advertising viewpoints (Verhoosel et al., 2016). Constrained limit with respect to gathering of pertinent data from social media platforms and seamless incorporation of the collected data from a variety of sources is perceived to be a significant issue (Bennett, 2015).

5.2.1. Farm management

As researchers of big data indicate, either big or small, big data is also data (Devlin, 2012). To obtain its full value, big data must be supervised and analyzed. Wireless network innovations, IoT, and cloud infrastructure are the main means of data storage and big data production. The final usage of big data is to obtain the information that is embodied by big data. Without big data analytics, big data from agriculture would have very little meaning (Sun et al., 2013). Data from multiple sources should be assimilated into “data lagoons” in order to accomplish big data analytics. The data failures and data replication in this process of assimilation lead to the emergence of data quality problems. Fig. 9 highlights a number of raw data operations that are required to ascertain the data quality.

Since the emergence of data on an enormous scale from data warehouses or distribution centers, the purported data-rich, information poor (DRIP) issues have been unavoidable. The DRIP problem has been alleviated by the big-data approaches that have released information to bolster educated, yet, not really faultless or legitimate choices or decisions. Big data can be dependent on to convey long-haul benefits for business when completely coordinated with conventional information management and administration processes (Devlin, 2012). Big data handling relies upon conventional, process-interceded information and metadata to construct the specific situation and consistency required for significant use. Big data handling outcomes should be sent back to customary business procedures in order to empower this transition and advancement of modern agriculture.

5.2.2. Data chain

A broad range of problems must be resolved for big data applications that are frequently reported in the literature. In certain phases of the data chain, both the technological and the management problems can emerge, where management concerns in the subsequent phases of the data chain may become increasingly pervasive. Table 9 outlines the state-of-the-art characteristics of the applications of smart farming using big data and the major problems that have been established in the literature at any point in the big data chain. At the onset, the accessibility of big data for further exploration may be affected by technological problems related to the data structure, equipment, and knowledge standards. Governance problems, such as establishing responsibility and enforcement arrangements, are more problematic for business operations at the later phases.

5.2.3. Network management organization

The network management organization addresses the involved stakeholders’ conduct and discerns the ways in which it could be regulated, such as achieving the aims and purpose of the business process. Two interrelated elements are deemed relevant for the growth as well as further advancement of applications of big data, namely, the governance and the business model. The governance entails informal and formal cooperation arrangements inside the network of stakeholders. There are three different types of network governance (Lazzarini et al., 2001): discretionary management, standardization, and mutual adjustment. These types are consistent with the three facets of network governance that are offered in (Provan and Kenis, (2008)): the lead organizational network, the management network, and the shared participant-led network.

In (Osterwalder, (2004)), the business model is described as a tool that includes a collection of elements and their interconnections, enabling the rationale behind the money earned by a company to be expressed. The network-centered business model that builds on network theories of value is yet a different view of the business model. These theories take into account the non-financial and financial importance of business exchanges as well as transactions. Both viewpoints are important to manage the network for applications of big data.

5.2.4. Network management technology

The network management technology incorporates every computer, peripheral, and network that have been operated and needed in order to adequately manage the organizational monitoring concerning agricultural practices, software systems, application packages, protocols, technological, communication, and information standards, such as a model for reference and communication and code standards, etc. (Van der Vorst et al., 2005; Alladi et al., 2020a). The various components include:

- Data resources saved, and their information exchanged through shared databases.
- Services and information systems to enable us to use and manage such databases.
- Entire formal coding and message set.

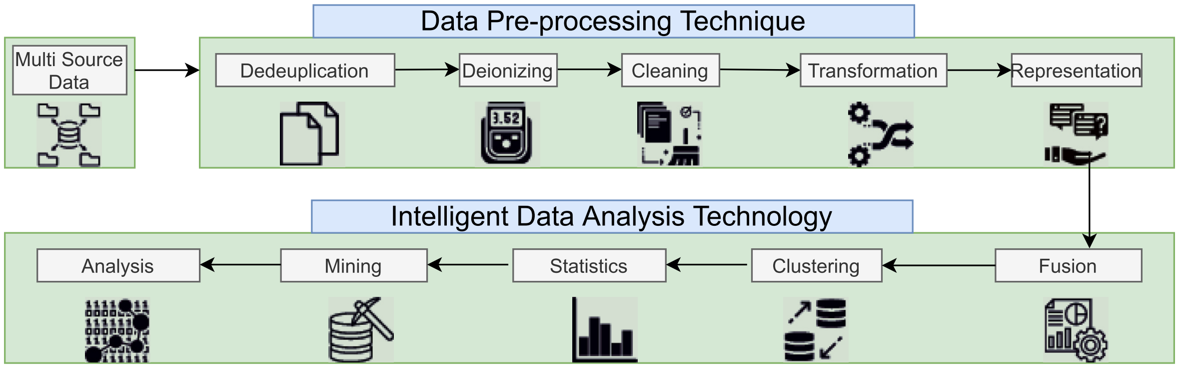

Fig. 9. Flowchart of different processing and analysis techniques of agricultural Big Data.

Table 9
Features and key issues of big data applications in Agriculture 4.0

Data Chain Stages	Features of Big Data applications	Key Issues
Record Information	Sensors Open Information UAVs data Biometric sensor data Genotype data Reciprocal Information	Availability Quality Formats
Store Information	Cloud based platform Hadoop Distributed File System (HDFS) Hybrid Storage Data Cloud-based data warehouse	Speed and safety of data access Expense
Transfer Information	Wireless Cloud-based platform Linked open Data	Security Agreements on responsibilities and liabilities
Modification of Information	ML Algorithms Normalization, Visualization and anonymization	Disparateness among data sources Automating data preparation and cleaning
Analysis ofInformation	Yield models Planting instructions Benchmarking Decision ontologies Cognitive Computing	Semantic heterogeneity Real-time analysis Scalability
Marketing Information	Information Visualization	Ownership Privacy New business models

- The essential infrastructure.

The use of big data techniques and methodologies in agriculture presents a prime opportunity to use the technological stack, to invest, and to realize the additional value in the agriculture sector (Noyes, 2014), (Sun et al., 2013). Big data applications in agriculture do not deal solely with the production of the crop. They also play a significant part in enhancing the overall effectiveness of the complete chain of supply and mitigating fears regarding the security of food (Chen et al., 2014a; Esmeijer et al., 2015). Performance measurement, predictive modeling, sensor installation and analytics, and the use of better systems to handle damage to crops and strengthen feed intake for cattle production are some of the possibilities for applications of big data in agriculture (Faulkner et al., 2014; Lesser, 2014). Big data, in conclusion, aims to offer additional probabilistic insight into potential agricultural outcomes in order to stimulate business decisions in real-time and re-invent existing systems for quicker technological innovations and business strategies (Devlin, 2012).

6. Machine learning approaches in agriculture 4.0

An essential goal of the PA is enhancing crop quality and production, at the same time lowering operating costs as well as environmental pollution at the same time. The prospects of crop yield and growth depend on numerous different attributes of production like weather, irrigation, topography, soil, and fertilizer management. In agriculture, accurate estimates of yield and optimal management of nitrogen are crucial. Remote sensing solutions are being utilized to enhance productivity and nitrogen control by helping construct the tools for decision-making for modern agricultural systems. However, remote-sensing-dependent solutions need vast volumes of remote-sensed data from different systems to be processed. The quantity increasing exponentially is beyond our capability to assimilate, analyze, and provide the best educated decisions. This is especially true if data are not homogeneous, that is sensors with various spatial, time, and spectral modalities are sensed. The modern technology of Machine Learning is capable of helping in identifying rules and trends in massive datasets (Zhang, 2006).

6.1. Advantages of machine learning

One of the key benefits of ML is its potential to resolve foremost non-linear problems autonomously by utilizing datasets from several connected resources. Several ML technologies such as Gaussian Processes (GPs) (Bishop, 2006), Indian Buffet Process (IBP) (Griffiths and Ghahramani, 2011), and Dirichlet Processes (DPs) (Ferguson, 1973) are probabilistic in nature and allow sensor noise to be considered when a probabilistic fusion of data from distinct sensors occurs. ML facilitates effective decision-making and intelligent behaviour with fairly less human interference in real-world scenarios. ML provides a robust and versatile structure for data-driven decision-making and also for integrates professional expertise with the framework. These are the primary features of ML methods, which render them extensively utilized and highly relevant to PA across several domains.

The ML techniques used to diagnose biotic stress early in crops, in particular for the purpose of detecting plant ailments, weeds, and pests, have been extensively examined in (Behmann et al., (2015)). The dilemma of the pre-planting vulnerability for the Stagonospora nodorum blotch (SNB) in winter wheat was tackled by ML techniques such as Artificial Neural Networks (ANNs), Random Forests (RFs), and Categorical and Regression Trees in (Mehra et al., (2016)). They also established models for risk evaluation, which are useful to determine disease control decisions before wheat crops are planted. The automated decision-making method for identifying weeds in maize crops based on the Bayesian system can save money as well as decrease pollution (Tellaeche et al., 2008).

In order to demonstrate structural and physiological characteristics of plants and facilitate the monitoring of physiological variability due to environmental impact, ML technologies applied to data of hyper-spectral imaging can be utilized. In (Goldstein et al., (2018)), it was illustrated that in order to provide automatic irrigation recommendations, field details, such as moisture of the soil, temperature, irrigation characteristics, and resultant production, could be combined using ML techniques (Ullah et al., 2021; BENYEZZA et al., 2021). A modern approach has been established in (Gutiérrez et al., (2018)) to determine the on-the-go state of the water present in vineyards with the capability to make irrigation decisions. This approach employs thermal imaging

Table 10
Publications that use ML techniques for crop yield estimation with a focus on their technical aspects.

Publication	Summary	Discussion
Kaul et al. (Kaul et al., 2005)	Serves as a reliable predictor for the output of maize and soybean. Results showed that the prediction of ANN yield is more exact than the model of Multiple Linear Regression (MLR) yield. **Methodology Used:** ANNs, MLR	MLR and ANN are the techniques for modelling and prediction in agriculture
Papageor. et al. (Papageorgiou et al., 2011)	Siz years of data used for the estimation of the average yield using the Fuzzy Gognitive Maps (FCM) soft computing methodology. Comparison checks on the all-round performance of every system showed the FCM solution was superior in majority of the cases. **Methodology Used:** FCM, ANNs, DTs, Bayesian Networks (BNs)	FCM can be used for representing information and making decisions in complex processing environments. FCMs can be used for modelling and depicting cotton yield forecast and crop management expertise
Heremans et al. (Heremans et al., 2015)	The intention was to estimate the capacity of winter wheat yield using two regression tree methods - Boosted Regression Trees (BRT) and Random Forest (RF), along with using spot-vegetation sensor, NDVI data, meteorological variables and levels of fertilization in northern China. The method based on cross validation of R-squared (R2) and Root Mean Square Error (RMSE) is used for evaluating. **Methodology Used:** BRT, RF	The results showed that RF for four of the five prefectures performed better than BRT. BRT is noise-sensitive, overfitting-prone, and much slower than bagging. RF can be used to enhance bagging performance.
Liang et al. (Liang et al., 2015)	The paper proposed a non-destructive approach for calculating the leaf area index (LAI) values of crops –a hybrid inversion process. The method used various regression algorithms to determine the relationship between simulated VIs and simulated LAI values. ANN and Random Forest Regression (RFR) were used to create hybrid inversion models. **Methodology Used:** Curve Fitting, ANNs, RFR	Analysis of the algorithms used revealed a better way of predicting RFR with specific data sets and specific VI with a higher R2 and lower RMSE
Wu et al. (Wu et al., 2015)	In order to measure LAI for the temperate meadow steppe in China the paper established and compared 2 inversion models based on the Linear Regression and BPNN models. BPNN (precision: 82.2% appeared to outdo Statistical Regression (precision: 78.8% **Methodology Used**: Statistical Regression, BPNN	BPNN refers to a broad family of ANNs where an error is measured at the output layer and is propagated back through the layers of the ANN. The weight of each layer is modified by optimization phase reducing the predefined loss feature.
Stas et al. (Stas et al., 2016)	Compared two ML technologies, BRT and Support Vector Machines (SVM) for the analysis of winter wheat yield prediction in the Henan province of China. Three kinds of NDVI-related predictors are used: Single NDVI, Incremental NDVI and Targeted NDVI. The comparison results, based on RMSE, showed that the BRT model consistently surpassed SVM. **Methodology Used:** BRT, SVM	When small amounts of training samples are available, the paper's ML techniques could manage a wide variety of predictors better than MLR.
Jin et al. (Jin et al., 2016)	The paper used the Particle Swarm Optimization (PSO) algorithm for the assimilation of field spectroscopic data into the AquaCrop model to increase the accuracy of predicting the outcome of winter wheat throughout various plantation dates and irrigation management strategies. **Methodology Used:** Particle Swarm Optimization (PSO)	Experiments showed the PSO algorithm as an efficient means of boosting the biomass and winter wheat yield forecasts. PSO can minimize the difference between the regression based and the AquaCrop model based estimates.
Li et al. (Li et al., 2016)	This paper aims to generate accurate and timely predictions for grassland LAI for the meadow steppes of northern China, using various strategies of regression and hybrid geostatistic techniques.The predictions were compared using hybrid geostatistical methods, followed by various regression models. The results show that the RF model gives predictions of regression models that are most precise. **Methodology Used:** Partial Least Squares Regression (PLSR), RFs, Regression Kriging (RK), Random Forests Residuals Kriging (RFRK)	RFs can have greater resistance than other regression approaches to over-fitting and noise problems. However, spatial autocorrelation information is ignored by the RF method. RFRK is an extension of RF and is similar to RK. It supports the inclusion of spatial autocorrelation in the RF.

and composition of ML strategies, Decision Trees (DTs), and Rotation Forests.

6.2. Yield estimation using machine learning

One of the primary goals of agricultural productivity is to maximize crop yield in a balanced environment at a minimized cost. Early recognition and maintenance of crop yield-related problems may significantly enhance yield and profits, and predicting yield is critical in various management decisions of crops and businesses. Various methods for ML have been introduced recently for the precise prediction of yields for different crops (Mishra et al., 2016). ANNs (Fortin et al., 2011), k-nearest neighbour (Zhang et al., 2010), and Support Vector Regression (SVR) (Ruβ, 2009) are the most effective ML methodologies. Although soil and weather conditions contribute significantly to crop growth and yields, still internet-based contiguous soil sensing is a missing factor in the management method for estimating pertinent soil characteristics. The variability of the yield of wheat using internet-based multi-layer soil details and the features of satellite imagery for the growth of crops are envisioned in (Pantazi et al., (2016)). Regulated Self Organizing Maps (SOMs) were used throughout this research. Data was utilized from an isolated cultivation period, and the efficiency of counter propagation artificial neural networks (CPANN), Supervised Kohonen networks (SKN), and XY-fused Networks (XY-F) in wheat yield predictions were contrasted. The average cumulative SKN precision was 81.65 percent, 78.3 percent for CPANN, and 80.92 percent for XY-F. The highest combined result was seen in the SKN model.

Spectral VIs are predominantly green, red, and infrared bands that are combined mathematically. These are intended to define functional relations between crop attributes and remote sensing measurements. Many vegetation indices, such as Normalized Difference Water Index (NDWI) (Satir and Berberoglu, 2016) and two-band Enhanced Vegetation Index (EVI2) (Bolton and Friedl, 2013), have been created since the development of NDVI and Simple Ratio Index (SR). A large array of indices are required to optimize the selection and combination of indices for a highly accurate estimation of crop yield.

Simulation of Back-propagation Neural Network (BPNN) was applied in (Panda et al., (2010)) in order to monitor the performance of four spectral VIs for yield prediction of the corn crop. The four VIs monitored were NDVI, soil adjusted vegetation index (SAVI), green vegetation index (GVI), and perpendicular vegetation index (PVI). The results demonstrated that the corn yield is better estimated with BPNN models, which use the standard deviations and means of PVI grid photographs. Some research to predict crop yields with ML techniques using data that is remotely sensed or is in-situ has been performed. Table 10 includes an analysis of the research carried out and summarizes the discussion of the various technical aspects of the ML methodologies that were used.

6.3. Use of machine learning for precision nitrogen management

Nitrogen (N) is of considerable significance for crop growth and health because it assumes an important part in the photosynthesis cycle. However, environmental concerns and other expenditures call for a cautious usage of nitrogen. The issue of optimum nitrogen management is attributed to these factors and has gained the attention of many researchers over time (Cao et al., 2017; Dai et al., 2013; Magney et al., 2017). One of the nitrogen management strategies in PA is using management or control zones, which implies defining subfield areas with homogenous traits needing similar care. Fuzzy C-means and k-means algorithms (Schuster et al., 2011) are by far the most commonly employed approaches to demarcate site-specific control zones. These are widely used clustering techniques for unsupervised learning and systemic recognition in datasets. Nonetheless, identifying subfield areas is a daunting challenge as the soil characteristics and nutrient levels are dynamic associations and also because of spatial variations that are culpable for the crop yield alterations in the region.

The non-destructive strategies used to make suggestions for the application of nitrogen fertilizer to crops generally are dependent on measures for plant nitrogen status by means of remote sensing or in situ data (Cilia et al., 2014; Maresma et al., 2016; Tremblay et al., 2011). In order to assess the nitrogen level of winter wheat, two sensor systems have been analyzed in (Cao et al., (2015)), which are premised upon a two fixed-band Green Seeker sensor and a 3-band Crop Circle ACS-470 sensor. Comparative results indicated that the nitrogen level of winter wheat could be strengthened by using the Crop Circle ACS-470 sensor. The benefits and drawbacks of the various approaches for discerning the nitrogen level of plants are thoroughly reviewed in (Muñoz-Huerta et al., (2013)). In (Diacono et al., (2013)), an assessment of the management of precision nitrogen in the wheat field is carried out. In order to evaluate both its performance and resilience, they analyzed strategies and outcomes of the site-specific management of nitrogen in wheat.

GPs ML regression algorithms have been used to determine the level of chlorophyll, nitrogen, and leaf water level from a multi-species, field-based dataset for trees (Van Wittenberghe et al., 2014). In order to estimate various leaf metrics, the GP used the whole spectral data and numerous spontaneously selected different wavebands as an input. Results demonstrate that the data for forecasting a leaf metric is not limited to one or more different bands. Instead, it can include six or more distinct bands equally. There are three methodologies, namely, Partial Least Squares (PLS), ANN, and Least-Squares SVM (LS-SVM), that have been used for calculating rice nitrogen status using spectra-reflectance canopy with visible and NIR reflectance spectroscopy (Shao et al., 2012). The relative analysis revealed that the LS-SVM exceeded the other methodologies and found LS-SVM to be a viable substitute for regression analysis in order to evaluate the status of nitrogen in the rice.

Although ML has recently developed in significant ways and is successful in many fields, the use of ML techniques is naively data-driven. The precision and the dubiousness of the predictions made by the ML algorithms rely heavily on the quality of the data, the representativeness of the model, and the correlations between the inputs and targets in the dataset obtained. The predictive ability of the models can be greatly diminished by excessive noise, inaccurate data, the existence of outliers and partiality in the results, and insufficient data sets. An adequate description of the ML model, for example, a GP covariance function, SVR parameters, and ANN design, is also important for optimum results. A variety of approaches may be used to resolve these limitations, such as integration of professional expertise into the covariance function, transfer learning, outlier identification, and simulation by means of automatic cross-validation.

7. Deep learning in agriculture 4.0

Deep learning (DL) is a popular and innovative technology showing great results and a high potential for image recognition and data analysis. Since DL has been implemented successfully in many fields, it has recently entered the field of agriculture. DL expands the conventional ML by introducing more complexity, and translating data through multiple layers of abstraction through numerous functions for representing data hierarchically (Schmidhuber, 2015). DL has a significant benefit in the form of feature-learning, i.e., the automated retrieval of raw data, with the configuration of lower-level functions making up the higher hierarchical levels (LeCun et al., 2015). Due to the more sophisticated models which permit significant parallelization, DL can respond to the challenges immediately and efficiently (Pan and Yang, 2010). Such sophisticated systems in DL can enhance the accuracy of classification or minimize regression errors if appropriate data sets are accessible to explain the problem.

DL comprises a number of different elements based on the network design, whether they are Unsupervised Pre-trained Networks, Recurrent Neural Networks, Convolutional Neural Networks, or Recursive Neural Networks. These elements are convolutions, connected layers, pooling layers, gateways, memory cells, triggering functions, encoding or decoding processes, etc. The inherent hierarchical nature of DL models and their learning capacities make them efficient in classification and estimation, also making them robust and responsive to a broad range of highly complex data analysis problems (Pan and Yang, 2010). While DL is widely present in numerous raster-based data applications, it can be used in any data format, such as audio, voice, and natural language, or, in general, for discrete or continuous data, like weather data (Sehgal et al., 2017), population data (Demmers et al., 2012), and soil chemistry (Song et al., 2016).

There are a number of existing prominent and established architectures, which researchers can utilize instead of starting anew to build their systems. These are AlexNet (Krizhevsky et al., 2017), GoogleNet (Szegedy et al., 2015), CaffeNet (Jia et al., 2014), and Inception-ResNet (Szegedy et al., 2017), etc. Every architecture has different benefits, which defines the appropriate scenario where it can be used (Canziani et al., 2016). It should also be noted that almost all the above models mentioned have pre-trained weights, indicating that their networks are already trained with certain datasets and so have learned to distinguish such problem areas accurately (Pan and Yang, 2010). Some widely used datasets for pre-training the DL models are PASCAL VOC (roject. 2012., 2012) and ImageNet (Deng et al., 2009). In Table 11, a few of the most common and free web-based datasets are available, which researchers can download to test their respective DL models. Such datasets can be utilized for pre-training the DL models and attune them to address potential problems in agriculture.

7.1. Related work in the field of deep learning in agriculture

In total, seventeen areas were discovered, with the common ones being land cover classification, weed identification, fruit counting, plant recognition, and classification of the type of crops. It is noteworthy that all articles, except (Demmers et al., 2012) and (Chen et al., 2014b), pertaining to the areas identified, were published after or during 2015, demonstrating how the latest and new this technology really is in the agricultural sector. The vast bulk of papers are concerned with identifying areas of interest. The areas of interest include fruit counting (Rahnemoonfar and Sheppard, 2017), obstacle detection (Steen et al., 2016; Christiansen et al., 2016), and the classification of the image. Several articles concentrate on forecasting future parameters, such as the yield of corn (Kuwata and Shibasaki, 2015), weather conditions (Sehgal et al., 2017), and on-field soil moisture content (Song et al., 2016). Most papers focus on crops from another viewpoint, while few papers consider issues like land cover, weed detection, soil research, livestock farming, weather prediction, and obstacle detection.

In order for DL models to be capable of distinguishing characteristics and attributes and performing precise classifications, variability between classes is required (Anand et al., 2021). Consequently, performance is positively associated with class variance. In (Luus et al., (2015)), a high correlation was identified between some classes of land cover, that is, buildings with medium density and dense residential buildings and storage tanks, while in (Ienco et al., (2017)), it was found that truck farming, summer crops, and tree crops were extremely mixed classes. In addition, some specific views of the plants, that is, leaf scans and flowers give different accuracy of classification than stems, branches, and images of the whole plant. One major problem in the identification of plant phenology is perhaps the reality that representations transform quite slowly, and it is difficult to discern images lying within the lengths of two successive stages (Yalcin, 2017). An akin problem materializes while evaluating the standard of vegetative growth (Minh et al., 2017). Additionally, in the demanding challenge of counting fruits, the models are prone to severe deformation, unregulated illumination, and depth variation, including strong color resemblance between the fruit and leaves (Chen et al., 2017).

The related works listed in Table 12 indicate the agricultural research areas, the specific issues they tackle, the DL models and architectures adopted, the data sources used, the data classes and labels, the pre-processing and augmentation of data employed, the overall performance achieved by the adopted metrics, and comparison with other strategies, wherever possible (Kamilaris and Prenafeta-Boldú, 2018).

7.2. Advantages of deep learning

DL has many benefits, as illustrated in many survey papers, such as reducing efforts in feature engineering, the performance improvements of prediction, and classification problems in the works. Considerable time is required when engineering components by hand, an effort that is automatically carried out in DL. Besides, searching manually for good extractors of features often is not a simple and understandable job. For example, when estimating crop yield (Kuwata and Shibasaki, 2015), it was impossible to retrieve traits manually that seriously influenced crop production. It was also the case with assessing the moisture levels of soil (Song et al., 2016).

In addition, the DL models can generalize effectively. For example, in the case of counting fruits, the model learned to count explicitly (Rahnemoonfar and Sheppard, 2017). The model was powerful in the problem of banana leaf classification (Amara et al., 2017) under demanding circumstances such as complicated background, illumination, varying image resolution, orientation, and image size. The models were also sturdy against variability, occlusion, scale, and illumination in the fruits counting papers (Chen et al., 2017). The same mechanisms for identification may be utilized for a number of fruits that are circular, like mangoes, citrus, peaches, etc. The DeepAnomaly model was distinguished mainly by the ability to classify anomalies and artifacts, not just an assortment of artifacts identified before, but by exploiting the uniformity of farming fields to identify objects that may be large, remote, obscured, or unknown (Christiansen et al., 2016).

Although DL requires a longer time to learn than traditional methods like SVM and RF, its performance in testing is fairly fast. For example, the model took a lot longer to train in detecting obstacles and anomalies (Christiansen et al., 2016), but once it was trained, the testing time of the model was well below the testing time of SVM and K-Nearest Neighbours (KNN). Moreover, when we consider the time required to construct filters and mine characteristics manually, almost negligible time is spent to train CNN and record images (Sørensen et al., 2017).

Another benefit of DL is the potential of designing simulated data sets to train a model, which could be better built to solve problems in the real world. For instance, in the case of maize and weed identification in the field, the authors tackled the problem of overlapping plant leaves by modeling top-down images of intertwining plants against soil context (Dyrmann et al., 2016). Then the trained network was able to differentiate weeds, even under overlapping conditions, from maize (Manikanthanet al., 2021).

7.3. Limitations and disadvantages of deep learning

The requirement for large datasets that acts as the input in the process of training is a significant downside and constraint in the usage of the DL methods. While data improvement technologies can improve certain datasets with transformations that retain the labels, in practice, hundreds of images are needed at minimum, according to the severity of the problem being studied, that is, the quantity of classes, accuracy desired, etc. The authors of (Mohanty et al., (2016)) and (Sa et al., 2016) speculated on the need of even more diverse datasets for training in order to enhance the precision of classification. A big issue for many datasets is the poor distinction between various classes (Yalcin, 2017) or the presence of noise, imprecision of sensory equipment (Song et al., 2016), clustering, plants overlapping, etc.

Another limitation is the capability of DL models to learn certain problems extremely well, even make generalizations in a few ways, but not being able to generalize outside of the limits of the expressiveness of the dataset. For instance, categorization of individual leaves, which are upward-facing against a homogenous background is done in (Mohanty et al., (2016)). The use in the real world should be its ability to recognize images of the disease straight from the plants. Many diseases are not visible on the top side of the leaves. For example, environmental factors like wilted leaf surfaces and damage by the insects significantly affected the identification of plants in (Lee et al., (2015)).

A common concern in computer vision, not just in DL, is that preprocessing of data is indeed a time-taking as well as a necessary task,

Table 11
Some agricultural datasets that are available for public use.

Dataset	Description of dataset	Source
Africa Soil InformationService (AFSIS) dataset	Sub-Saharan Africa soil maps in a digital ~ format	Data – Africa Soil Infor
Crop/Weed Field Image Dataset	Images, segmentation masks and plant type descriptions of crops and weeds	Haug and Ostermann (2015)
EPFL, Plant VillageDataset	Crop images and their ailments	EPFL
Flavia leaf dataset	Leaf images from 32 plants	Flaviaeaf Recogniti
Image-Net Dataset	Images of different plants, trees, flowers or vegetables	Image-Net Dataset: Image
ImageNet Large Scale Visual Recognition Challenge (ILSVRC)	Images to locate and identifyartifacts	Russakovsky et al. (2015)
Leafsnap Dataset	Leaves of 185 north-eastern American tree species	Leafsnap Dataset — Leafs
LifeCLEF Dataset	Identification of spatial distributionand plant applications	Plant task — Image/ (2014)
MalayaKew Dataset	Scanned leaf images from 44 different species	Chee Seng Chan - Plant D
PASCAL Visual Object Classes Dataset	Images of different animals and birds	PASCAL Visual Project
Syngenta Crop "Syngenta Crop Challenge, 2017	Corn hybrids in 2122 locations during the period from 2008 to 2016, along with weather and soil data	Syngenta Crop Challenge (2017)
University of Arcansas, Plants Dataset	Image database for herbicide damage	U of A Herbicide Injury Photo Database
UC Merced Land Use Dataset	Using image details from a 21-class property	UC Merced Land Use Dataset
University of Bonn Photogrammetry, IGG	Sugar beets data set for ~ positioning and visualization, for plant classification	University of Bonn Photogrammetry

Table 12
Deep learning applications in agriculture.

Agricultural Area	Explanation of Dataset Used	Classes and Labels in Dataset	Deep Learning Model Used
Research on animals	160 pigs, kept in 2 rooms with climate control, 4 pens per room, 10 pigs per pen. Ammonia, indoor air temperature and humidity, and airing measured at intervals of 6 min.	Estimation of the weight of pigs	First-order Deep Recurrent Neural Network (DRNN)
Classification and detection of crop or weed	Computer-generated top-down images of plants overlapping against soil background. 301 images of soil and 8430 images of 23 species of weed and maize.	Image patch identification whether it belongs to soil, weed, or maize crop	Adapted version of VGG16 Convolutional Neural Networks (CNN)
Classification of crop type	Aerial images of farms obtained from an experiment series conducted by the Agroscope research center of Swiss Confederation's.	23 classes: 22 different crops and soil	CNN + HistNN (using RGB histograms)
Counting of fruits	Authors produced 24,000 synthetic images.	Number of tomatoes prediction	A Modified Inception- ResNet CNN
Classification of leaves	1907 leaf images of 32 species with fifty images per species from Flavia dataset.	32 classes: 32 different species of plant	Author-defined CNN + RF classifier
Detection of diseases in leaves	4483 images contained in a database created by authors.	15 classes: 13 plant diseases, 1 healthy leaves, 1 background images	CaffeNet CNN
Classification of land cover	Dataset 1 is a A mixture of vegetation sites over KSC, FL, USA. Dataset 2 is an urban site over the city of Pavia, Italy. Hyperspectral datasets.	Thirteen land-cover classes in Dataset 1, Nine land cover classes of trees in Dataset 2: Soil, shadows, meadow, water, different materials	Hybrid of PCA, autoencoder (AE), and logistic regression
Detection of obstacles	48 images of background data and 48 images of test data from observations of humans, barrels, houses, mannequins, and wells.	Each pixel is classified as either foreground, i.e. containing a human or background i.e., anomaly detection	AlexNet and VGG CNNs
Content of soil moisture prediction	Soil data obtained from corn field that is irrigated in the Zhangye oasis, Northwest China.	Soil moisture content (SMC) in percentage	Deep belief network based macroscopic cellular automata (DBNMCA)
Recognition of plants	INTA Argentina provided 866 images of leaves. Dataset is partitioned into 3 classes: soybean leaves (422 images), red bean leaves (272 images) and white bean leaves (172 images).	Three classes: Legume species of white bean, soybean and red bean	Author-defined CNN
Root and soil segmentation	X-ray tomography soil images.	Two classes: Root or soil	Author-defined CNN with SVM for classification
Weather forecasting	Syngenta Crop Challenge 2016 dataset, which has 6490 sub-regions having 3 attributes for weather condition from the years 2000–2015.	Prediction of temperature, precipitation and solar radiation values	LSTM

particularly when it involves satellite or aerial images. Their limited training samples and high dimensionality are a problem with data that is hyperspectral (Chen et al., 2014b). In fact, the current databases often don't thoroughly explain the issue they are targeting (Song et al., 2016). For example, to estimate corn yield (Kuwata and Shibasaki, 2015), it was important to take into consideration the external factors by entering information of farming such as irrigation and fertilization (Kashyap et al., 2021).

Table 13 lists several current computer vision applications in agriculture. We can observe that merely the classification issues related to land cover, estimation of crop type, weed detection, crop phenology, and fruit grading are estimated using DL (Kamilaris and Prenafeta-Boldú, 2018). DL has application in many other agricultural issues described, such as the content of nitrogen in soil and leaf, seeds identification, detection of water stress in plants, irrigation, detection of pest, herbicide use, water erosion assessment, food or disease defects, crop-hail damage, contaminant identification, and monitoring greenhouse. Instinctively, as many of the research areas referred above use data analysis approaches with similar principles and comparable efficiencies to DL, such as logistic and linear regression, KNN, SVM, K-means clustering, Fourier transform, and Wavelet-based filtering (Singh et al., 2016), it may be worth exploring the applicability of DL on these issues as well.

8. Challenges and future trends in agriculture 4.0

From our review and studies of ongoing developments in the field of IoT applications in agriculture, we identify challenges and possible future trends depending on different state-of-the-art technologies which exist and have been addressed in our survey in the area of Agriculture 4.0.

8.1. Innovation in technology

Countless IoT solutions would continue to evolve, and innovative technologies will be implemented, especially in the agricultural sector. Developing an IoT platform for the purpose of agriculture would change from catering to only particular livestock or crops to a platform which is universal and can support any livestock or crop. It would allow for an easily modifiable system that can endorse a diverse range of applications from crop and livestock management and monitoring to the merchandising of products to consumers and local shops. Such a system would be independent of any regional and geographical limitations and therefore can serve as the facilitator for several IoT applications in agriculture. IoT devices, software platforms are currently being developed, and research efforts are underway into communication technologies which can deliver IoT deployments at low costs. Much of the latest research relates to small-scale testing and prototyping. For assessing the usefulness and usability of IoT technologies in agriculture, large-scale pilots are required. Future work would see more of a large-scale pilot in the overall agro-food applications and supply chains, not just in the developed countries, but in the developing countries of Africa and Asia as well.

8.2. Challenges and trends in UAVs and thermal remote sensing

Given that UAVs have recently entered in the market for applications in agriculture, numerous studies, the progress, and subjects addressed are impressive, and also majority of studies validate the immense prospective of UAVs in precision farming (Alladi et al., 2020b). Although (nano)satellites would also provide elevated spatial and temporal resolution, UAVs possess many distinctive characteristics to provide remote data sensing in precision farming by keeping them in pole position. In addition to the competitive pricing, UAVs are still unique in.

- offering resolution in centimetres
- combining the canopy height with the orthophoto detail

Table 13
Computer vision applications in agriculture and popular data analysis techniques.

Agriculture Application	Remote Sensing Technique	Data Analysis Technique
Expansion in Agriculture	Satellite Remote Sensing	Wavelet-based filtering
Crop hail damage	Polarimetric radar imageryMulti Spectral imaging	Unsupervised Image ClassificationLinear and exponential Regression analysis
Crop Phenology	Satellite remote sensing	NDVIFourier transformsWavelet-based filtering
Fruit Grading	Monochronic imagesOptical cameras	K-means clusteringLDAImage fusionBayesian discriminant analysis
Monitoring of greenhouse	Optical camerasThermal Cameras	NDVILinear and exponential Regression analysisIR thermographyUnsupervised classification
Herbicide	Optical CamerasPhoto-detectorsRemote sensing	Discriminant AnalysisFuzzy techniques
Seed identification and species reorganization	Hyperspectral ImagingCameras and photo-detectors	Principal Component AnalysisLinear regression AnalysisFeature extraction
Irrigation	Satellite remote sensingThermal InfraredRed-edge cameras	NDVIImage classification techniquesLinear Regression AnalysisDecision Trees
Indexing of leaf area	Multi-spectralimaging Hyperspectralimaging	NDVILinear regressionanalysis
Detection of water stressin plants and droughtconditions	Satellite remote sensingNIR camera Thermal imaging	Fraunhofer LineDepth (FLD) principleNDVILinear regressionanalysis
Detection of pests	Thermal cameraMicrowave remotesensing	Cross-entropy method (CEM)nonlinear signal processing StatisticalanalysisLinear andexponential regression analysis
Mapping of soil andcrops	Hyperspectralimaging SAR Multispectralimaging	Image fusionDistance-basedclassificationEnd-memberextraction algorithmLinearpolarizations (HH, VV, HV)Co-polarized phasedifferences (PPD)
Assessment of watererosion	Satellite remotesensing NIR cameraSAR	Interferometric SARimage processingContour tracingLinear and exponentialregression analysis
Detection of weeds	Hyperspectral and multi-spectral imaging Optical camerasPhoto-detectors	ANNsTechniques of featureextraction with FFTErosion anddilation segmentationGenetic algorithms Wavelet-basedclassification and Gabor filtering

- providing multi-angle data (especially from snapshot cameras)
- gathering hyperspectral data of high quality
- the sensors' adaptability

In particular, UAVs would remain or turn into a standard platform for applications which require thermal, extremely high resolution, or hyperspectral data, like weed detection, premature detection of drought stress, and early exposure of pathogen. For application fields where multispectral imagery of medium resolution is sufficient, like monitoring of biomass, assessment of nutrient status, or prediction of yield, UAVs would be one of the available platforms, besides (nano)satellites and probably tractor based sensors. While thermal remote sensing does have ability to provide spatiotemporal information about the temperature of the soil and crop surface, there are a few issues which need to be addressed when using thermal images. These comprise the impacts of:

1. temporal and spatial resolutions of obtained images
2. atmospheric conditions
3. thermal sensor's altitude and viewing angle
4. stage of crop growth and variation of crop species

Thermal images are also accessible at high spectral, temporal and spatial resolutions at a lesser price relative to the previous years, due to recent advances in UAVs. In future, the usage of UAVs for soil and crop supervising is expected to rise dramatically when compared to conventional satellite and manned-aircrafts because of the versatility and low price for image accession.

8.3. Research areas in IoUT deployment

More research could be done in the field of implementation and design of PA based IoUT systems to address the challenges mentioned below.

- Low-complexity and low-cost IoUT devices with the capability to sustain rugged terrains in every type of soil moisture regimes are appealing because of the wide area of operation in agricultural fields.
- Upgrading UTs with a range of complex functionalities would result in increased energy consumption and rapid degradation of the batteries. So, betterments in energy efficient services, renewable resources of energy, and reaping of energy are the major challenges.
- Their integration with the communications systems is a significant challenge pertaining to the availability of various kinds of SM sensors. The smooth incorporation of various types of sensors with the communications systems in IoUT requires a standard protocol.
- Sophisticated security implementations are needed to guard the data which is transferred within the farms. In addition, field-based privacy approaches are needed in such a way that data from different farms could be combined for greater precise decisions while protecting growers' privacy.

8.4. Future trends in machine learning and data analytics

The below future trends could be predicted on the basis of the latest dynamics in algorithmic advances and sensor technologies:

- More tailored, focused application to specific PA tasks of the proven ML techniques and currently available sensors.
- Interconnected treatment of spectral, temporal and spatial domains and the inclusion of expertise in ML techniques targeted at modelling and decision-making in various features of PA.
- Spectral and spatial fusion of sensor information, with different spectral features and spatial resolution.
- Complex blend of mobile (such as aerial and land vehicles) and stationary (such as in-ground sensors and weather station) equipment for enabling data collection actively and optimally, fusion of information and upgrading of models for high value areas.
- More work on using artificial intelligence to model disease management and crop growth based on climate information and farm data is expected.
- DA algorithms are expected to be built which can process large volumes of data at a much greater rate compared to the time of IoT communication.
- Business models which are appealing enough for providers of solutions and also facilitate fair sharing among the various stakeholders.
- Accessibility of platforms which would speed up the innovation and development of solutions and also strengthen farmers position in the supply chain.

9. Conclusion

Given the increasing food requirements of the rising world population and decreasing agricultural land, an emphasis on smarter, healthier, and more efficient crop production methods and techniques are required. The various Agriculture 4.0 approaches to enhance crop yields and cultivation practices are very promising in this regard. Crop growth monitoring, nutrition, health labeling, and collaboration amongst farmers, pluckers, packagers, transporters, distributors, warehouses, and end-consumers have all been made possible by using agriculture 4.0. Farming as a career choice is becoming popular amongst scientific and creative young people with the adoption of Agriculture 4.0. Agriculture has become an extremely data-intensive field, with inputs from numerous farm machinery and devices, sensors, and weather stations. This survey considered all these facets and illustrated the functions of different technologies involved in Agriculture 4.0. In particular, the use of IoT in Agriculture is instrumental in making the agricultural sector smarter and better suited for future prospects. The agricultural sector is expected to benefit from IoT in a number of ways. However, various problems must be tackled for small and medium-scale farmers to afford it. Security and cost are the most important considerations. The adoption rate of IoT in agriculture is expected to rise as competition in the agriculture sector increases, and favourable policies are introduced. It can be ascertained that earth has the resources, but we must learn to use them judiciously and efficiently. Strategic technology usage may contribute to the effective use of these assets and resources to facilitate the food sustainability for present and future generations.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Adão, T., Hruška, J., Pádua, L., Bessa, J., Peres, E., Morais, R., Sousa, J.J., 2017. Hyperspectral imaging: a review on uav-based sensors, data processing and applications for agriculture and forestry. Rem. Sens. 9 (11), 1110.

Akyildiz, I.F., Stuntebeck, E.P., 2006. Wireless underground sensor networks: research challenges. Ad Hoc Netw. 4 (6), 669–686.

Alfian, G., Syafrudin, M., Rhee, J., 2017. Real-time monitoring system using smartphone-based sensors and nosql database for perishable supply chain. Sustainability 9 (11), 2073.

Alladi, T., Chamola, V., Naren, Feb. 2021. HARCI: A Two-Way Authentication Protocol for Three Entity Healthcare IoT Networks. IEEE Journal on Selected Areas in Communications 39 (2), 361–369. https://doi.org/10.1109/JSAC.2020.3020605.

Alladi, T., Naren, N., Bansal, G., Chamola, V., Guizani, M., 2020b. Secauthuav: A Novel Authentication Scheme for Uav-Base Station Scenario. *IEEE Transactions on Vehicular Technology*.

Amara, J., Bouaziz, B., Algergawy, A., 2017. A Deep Learning-Based Approach for Banana Leaf Diseases Classification. Datenbanksysteme für Business, Technologie und Web (BTW 2017)-Workshopband.

Anand, T., Sinha, S., Mandal, M., Chamola, V., Richard Yu, F., 2021. Agrisegnet: deep aerial semantic segmentation framework for iot-assisted precision agriculture. IEEE Sensor. J. 1, 1.

Anderson, M.C., Hain, C., Otkin, J., Zhan, X., Mo, K., Svoboda, M., Wardlow, B., Pimstein, A., 2013. An intercomparison of drought indicators based on thermal remote sensing and nldas-2 simulations with us drought monitor classifications. J. Hydrometeorol. 14 (4), 1035–1056.

Ayaz, M., Ammad-Uddin, M., Baig, I., et al., 2017. "Wireless sensor's civil applications, prototypes, and future integration possibilities: a review. IEEE Sensor. J. 18 (1), 4–30.

Ayaz, M., Ammad-Uddin, M., Sharif, Z., Mansour, A., Aggoune, E.-H.M., 2019. Internet-of-things (iot)-based smart agriculture: toward making the fields talk. IEEE Access 7, 129 551–129 583.

Bac, C.W., Hemming, J., Van Tuijl, B., Barth, R., Wais, E., van Henten, E.J., 2017. Performance evaluation of a harvesting robot for sweet pepper. J. Field Robot. 34 (6), 1123–1139.

Bargoti, S., Underwood, J., 2017. Deep fruit detection in orchards. In: 2017 IEEE International Conference on Robotics and Automation (ICRA). IEEE, pp. 3626–3633.

Bartlett, A., Andales, A., Arabi, M., Bauder, T., 2015. A smartphone app to extend use of a cloud-based irrigation scheduling tool. Comput. Electron. Agric. 111, 127–130.

Basso, B., Ritchie, J., Pierce, F., Braga, R., Jones, J., 2001. Spatial validation of crop models for precision agriculture. Agric. Syst. 68 (2), 97–112.

Behmann, J., Mahlein, A.-K., Rumpf, T., Römer, C., Plümer, L., 2015. A review of advanced machine learning methods for the detection of biotic stress in precision crop protection. Precis. Agric. 16 (3), 239–260.

Bendre, M., Thool, R., Thool, V., 2015. Big data in precision agriculture: weather forecasting for future farming. In: 2015 1st International Conference on Next Generation Computing Technologies (NGCT). IEEE, pp. 744–750.

Bennett, J.M., 2015. Agricultural big data: utilisation to discover the unknown and instigate practice change. Farm Policy Journal 12 (1), 43–50.

Benyezza, H., Bouhedda, M., Rebouh, S., 2021. Zoning irrigation smart system based on fuzzy control technology and iot for water and energy saving. J. Clean. Prod. 127001.

Bishop, C.M., 2006. Pattern Recognition and Machine Learning. springer.

Bogena, H., Herbst, M., Huisman, J., Rosenbaum, U., Weuthen, A., Vereecken, H., 2010. Potential of wireless sensor networks for measuring soil water content variability. Vadose Zone J. 9 (4), 1002–1013.

Bolton, D.K., Friedl, M.A., 2013. Forecasting crop yield using remotely sensed vegetation indices and crop phenology metrics. Agric. For. Meteorol. 173, 74–84.

Bruns, H.A., 2017. Southern corn leaf blight: a story worth retelling. Agron. J. 109 (4), 1218–1224.

Bueno-Delgado, M.V., Molina-Martínez, J.M., Correoso-Campillo, R., Pavón-Mariño, P., 2016. Ecofert: An android application for the optimization of fertilizer cost in fertigation. Comput. Electron. Agric. 121, 32–42.

Cameron, D., Osborne, C., Horton, P., Sinclair, M., 2015. A sustainable model for intensive agriculture. Grantham Centre for Sustainable Futures 2.

Canziani, A., Paszke, A., Culurciello, E., 2016. An Analysis of Deep Neural Network Models for Practical Applications arXiv preprint arXiv:1605.07678.

Cao, Q., Miao, Y., Feng, G., Gao, X., Li, F., Liu, B., Yue, S., Cheng, S., Ustin, S.L., Khosla, R., 2015. Active canopy sensing of winter wheat nitrogen status: an evaluation of two sensor systems. Comput. Electron. Agric. 112, 54–67.

Cao, Q., Miao, Y., Li, F., Gao, X., Liu, B., Lu, D., Chen, X., 2017. Developing a new crop circle active canopy sensor-based precision nitrogen management strategy for winter wheat in north China plain. Precis. Agric. 18 (1), 2–18.

Carlson, T., 2007. "An overview of the" triangle method" for estimating surface evapotranspiration and soil moisture from satellite imagery. Sensors 7 (8), 1612–1629.

Carvalho, F.P., 2017. Pesticides, environment, and food safety. Food and Energy Security 6 (2), 48–60.

Ceballos, F., Kramer, B., Robles, M., 2019. The feasibility of picture-based insurance (pbi): smartphone pictures for affordable crop insurance. Development Engineering 4, 100042.

Chaerle, L., Hagenbeek, D., De Bruyne, E., Valcke, R., Van Der Straeten, D., 2004. Thermal and chlorophyll-fluorescence imaging distinguish plant-pathogen interactions at an early stage. Plant Cell Physiol. 45 (7), 887–896.

Chamola, V., Kotesh, P., Agarwal, A., Gupta, N., Guizani, M., et al., 2020. A Comprehensive Review of Unmanned Aerial Vehicle Attacks and Neutralization Techniques. *Ad Hoc Networks*, p. 102324.

Chávez, J.L., Neale, C.M., Prueger, J.H., Kustas, W.P., 2008. Daily evapotranspiration estimates from extrapolating instantaneous airborne remote sensing et values. Irrigat. Sci. 27 (1), 67–81.

Chen, M., Mao, S., Liu, Y., 2014a. Big data: a survey. Mobile Network. Appl. 19 (2), 171–209.

Chen, Y., Lin, Z., Zhao, X., Wang, G., Gu, Y., 2014b. Deep learning-based classification of hyperspectral data. IEEE Journal of Selected topics in applied earth observations and remote sensing 7 (6), 2094–2107.

Chen, S.W., Shivakumar, S.S., Dcunha, S., Das, J., Okon, E., Qu, C., Taylor, C.J., Kumar, V., 2017. Counting apples and oranges with deep learning: a data-driven approach. IEEE Robotics and Automation Letters 2 (2), 781–788.

Chen, X., Shi, Q., Yang, L., Xu, J., 2018. Thriftyedge: resource-efficient edge computing for intelligent iot applications. IEEE network 32 (1), 61–65.

Cho, Y., Cho, K., Shin, C., Park, J., Lee, E.-S., 2012. An agricultural expert cloud for a smart farm. In: Future Information Technology, Application, and Service. Springer, pp. 657–662.

Christiansen, P., Nielsen, L.N., Steen, K.A., Jørgensen, R.N., Karstoft, H., 2016. Deepanomaly: Combining background subtraction and deep learning for detecting obstacles and anomalies in an agricultural field. Sensors 16 (11), 1904.

Cilia, C., Panigada, C., Rossini, M., Meroni, M., Busetto, L., Amaducci, S., Boschetti, M., Picchi, V., Colombo, R., 2014. Nitrogen status assessment for variable rate fertilization in maize through hyperspectral imagery. Rem. Sens. 6 (7), 6549–6565.

Cozzolino, D., Porker, K., Laws, M., 2015. An overview on the use of infrared sensors for in field, proximal and at harvest monitoring of cereal crops. Agriculture 5 (3), 713–722.

Crookston, R., 2006. A top 10 list of developments and issues impacting crop management and ecology during the past 50 years. Crop Science - CROP SCI 46, 9.

Dai, X., Zhou, X., Jia, D., Xiao, L., Kong, H., He, M., 2013. Managing the seeding rate to improve nitrogen-use efficiency of winter wheat. Field Crop. Res. 154, 100–109.

de Oliveira, K.V., Castelli, H.M.E., Montebeller, S.J., Avancini, T.G.P., 2017. Wireless sensor network for smart agriculture using zigbee protocol,. In: 2017 IEEE First Summer School on Smart Cities (S3C). IEEE, pp. 61–66.

Demmers, T.G., Gauss, S., Wathes, C., Cao, Y., Parsons, D., et al., 2012. Simultaneous monitoring and control of pig growth and ammonia emissions. In: The Ninth International Livestock Environment Symposium (ILES IX). International Conference of Agricultural Engineering-CIGR-AgEng 2012: Agriculture and Engineering for a Healthier Life, Valencia, Spain, 8-12 July 2012. CIGR-EurAgEng.

Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., Fei-Fei, L., 2009. Imagenet: a large-scale hierarchical image database. In: 2009 IEEE Conference on Computer Vision and Pattern Recognition. Ieee, pp. 248–255.

Devlin, B., 2012. The Big Data Zoo–Taming the Beasts: the Need for an Integrated Platform for Enterprise Information. 9sight Consulting, *Cape Town*.

Diacono, M., Rubino, P., Montemurro, F., 2013. Precision nitrogen management of wheat. a review. Agron. Sustain. Dev. 33 (1), 219–241.
Dinkins, C.P., Jones, C., 2013. Interpretation of Soil Test Reports for Agriculture. MT200702AG, Montana State University Extension.
Dong, X., Vuran, M.C., Irmak, S., 2013. Autonomous precision agriculture through integration of wireless underground sensor networks with center pivot irrigation systems. Ad Hoc Netw. 11 (7), 1975–1987.
Dyrmann, M., Mortensen, A.K., Midtiby, H.S., Jørgensen, R.N., et al., 2016. Pixel-wise classification of weeds and crops in images by using a fully convolutional neural network. In: Proceedings of the International Conference on Agricultural Engineering. Aarhus, Denmark, pp. 26–29.
D'Oleire-Oltmanns, S., Marzolff, I., Peter, K.D., Ries, J.B., 2012. Unmanned aerial vehicle (uav) for monitoring soil erosion in Morocco. Rem. Sens. 4 (11), 3390–3416.
Elijah, O., Rahman, T.A., Orikumhi, I., Leow, C.Y., Hindia, M.N., 2018. An overview of internet of things (iot) and data analytics in agriculture: benefits and challenges. IEEE Internet of Things Journal 5 (5), 3758–3773.
Esmeijer, J., Bakker, T., Ooms, M., Kotterink, B., van Economische Zaken, S.M., 2015. Data-driven innovation in agriculture: case study for the oecd kbc2-programme. TNO Report TNO 10154.
Evans, D., 2011. The internet of things: how the next evolution of the internet is changing everything. CISCO white paper 1 (2011), 1–11.
Faiçal, B.S., Freitas, H., Gomes, P.H., Mano, L.Y., Pessin, G., de Carvalho, A.C., Krishnamachari, B., Ueyama, J., 2017. An adaptive approach for uav-based pesticide spraying in dynamic environments. Comput. Electron. Agric. 138, 210–223.
Farid, M., Alshawabkeh, A.N., Rappaport, C.M., 2006. Validation and calibration of a laboratory experimental setup for cross-well radar in sand. Geotech. Test J. 29 (2), 158–167.
Faulkner, A., Cebul, K., McHenry, G., 2014. Agriculture Gets Smart: the Rise of Data and Robotics. *Cleantech Agriculture Report*.
Feng, J., Zeng, L., He, L., 2019. Apple fruit recognition algorithm based on multi-spectral dynamic image analysis. Sensors 19 (4), 949.
Ferguson, T.S., 1973. A Bayesian Analysis of Some Nonparametric Problems. The annals of statistics, pp. 209–230.
Ferguson, J.C., Chechetto, R.G., O'Donnell, C.C., Fritz, B.K., Hoffmann, W.C., Coleman, C.E., Chauhan, B.S., Adkins, S.W., Kruger, G.R., Hewitt, A.J., 2016. "Assessing a novel smartphone application–snapcard, compared to five imaging systems to quantify droplet deposition on artificial collectors. Comput. Electron. Agric. 128, 193–198.
Fortin, J.G., Anctil, F., Parent, L.-É., Bolinder, M.A., 2011. Site-specific early season potato yield forecast by neural network in eastern Canada. Precis. Agric. 12 (6), 905–923.
Freebairn, D., Robinson, B., McClymont, D., Raine, S., Schmidt, E., Skowronski, V., Eberhard, J., et al., 2017. Soilwaterapp-monitoring soil water made easy. In: Proceedings of the 18th Australian Society of Agronomy Conference.
Garcia-Sanchez, A.-J., Garcia-Sanchez, F., Garcia-Haro, J., 2011. Wireless sensor network deployment for integrating video-surveillance and data-monitoring in precision agriculture over distributed crops. Comput. Electron. Agric. 75 (2), 288–303.
Gebbers, R., Adamchuk, V.I., 2010. Precision agriculture and food security. Science 327 (5967), 828–831.
Geipel, J., Link, J., Claupein, W., 2014. Combined spectral and spatial modeling of corn yield based on aerial images and crop surface models acquired with an unmanned aircraft system. Rem. Sens. 6 (11), 10 335–410 355.
Gershenfeld, N., Krikorian, R., Cohen, D., 2004. The internet of things. Sci. Am. 291 (4), 76–81.
Gill, R., 2021. A review on various techniques to transform traditional farming to precision agriculture. Turkish Journal of Computer and Mathematics Education (TURCOMAT) 12 (2), 131–135.
Gitelson, A.A., Gritz, Y., Merzlyak, M.N., 2003. Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. J. Plant Physiol. 160 (3), 271–282.
Goldstein, A., Fink, L., Meitin, A., Bohadana, S., Lutenberg, O., Ravid, G., 2018. "Applying machine learning on sensor data for irrigation recommendations: revealing the agronomist's tacit knowledge. Precis. Agric. 19 (3), 421–444.
Griffiths, T.L., Ghahramani, Z., 2011. The indian buffet process: an introduction and review. J. Mach. Learn. Res. 12 (4).
Grobart, S., 2012. Dairy Industry in Era of Big Data: New Gadgets Help Farmers Monitor Cows and Analyze Their Milk.
Gutiérrez, J., Villa-Medina, J.F., Nieto-Garibay, A., Porta-Gándara, M.Á., 2013. Automated irrigation system using a wireless sensor network and gprs module. IEEE transactions on instrumentation and measurement 63 (1), 166–176.
Gutiérrez, S., Diago, M.P., Fernández-Novales, J., Tardaguila, J., 2018. Vineyard water status assessment using on-the-go thermal imaging and machine learning. PloS One 13 (2), e0192037.
Hajare, R., Gowda, C.M., Sanjaya, M., 2021. Design and implementation of agricultural drone for areca nut farms. In: Advances in VLSI, Signal Processing, Power Electronics, IoT, Communication and Embedded Systems: Select Proceedings of VSPICE 2020, vol. 752, p. 251.
Hajirahimova, M.S., 2015. Opportunities and challenges big data in oil and gas industry. In: Proceedings of the National Supercomputer Forum (NSKF 2015), Russia. Pereslavl-Zalesskiy, pp. 24–27.
Hassija, V., Chamola, V., Saxena, V., Jain, D., Goyal, P., Sikdar, B., 2019. A survey on iot security: application areas, security threats, and solution architectures. IEEE Access 7, 82 721–782 743.
Hatfield, J.L., Prueger, J.H., 2010. Value of using different vegetative indices to quantify agricultural crop characteristics at different growth stages under varying management practices. Rem. Sens. 2 (2), 562–578.
Haug, S., Ostermann, J., 2015. A crop/weed field image dataset for the evaluation of computer vision based precision agriculture tasks. In: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 8928. Springer Verlag, pp. 105–116.
Heremans, S., Dong, Q., Zhang, B., Bydekerke, L., Van Orshoven, J., 2015. Potential of ensemble tree methods for early-season prediction of winter wheat yield from short time series of remotely sensed normalized difference vegetation index and in situ meteorological data. J. Appl. Remote Sens. 9 (1), 097095.
Herrick, J.E., Beh, A., Barrios, E., Bouvier, I., Coetzee, M., Dent, D., Elias, E., Hengl, T., Karl, J.W., Liniger, H., et al., 2016. The land-potential knowledge system (landpks): mobile apps and collaboration for optimizing climate change investments. Ecosys. Health Sustain. 2 (3), e01209.
Hillel, D., 2013. Advances in Irrigation:, vol. 2. Elsevier vol. 2.
Hively, W.D., 2015. Mapping Crop Residue and Tillage Intensity on Chesapeake Bay Farmland". http://eros.usgs.gov/doi-remotesensing-activities/2015/.
Hoffman, S., Erb, K., 2016. Mapping Tile Drainage Systems. University of Wisconsin Extension.
Hofstrand, D., 2010. Understanding the Economics of Tile Drainage. Ag Decision Maker, Iowa State University Extension.
Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002. Overview of the radiometric and biophysical performance of the modis vegetation indices. Rem. Sens. Environ. 83 (1–2), 195–213.
Ibayashi, H., Kaneda, Y., Imahara, J., Oishi, N., Kuroda, M., Mineno, H., 2016. A reliable wireless control system for tomato hydroponics. Sensors 16 (5), 644.
Ienco, D., Gaetano, R., Dupaquier, C., Maurel, P., 2017. Land cover classification via multitemporal spatial data by deep recurrent neural networks. Geosci. Rem. Sens. Lett. IEEE 14 (10), 1685–1689.
Iof2020. https://www.iof2020.eu/.
Irmak, S., 2015. "Interannual variation in long-term center pivot–irrigated maize evapotranspiration and various water productivity response indices. i: grain yield, actual and basal evapotranspiration, irrigation-yield production functions, evapotranspiration-yield production functions, and yield response factors. J. Irrigat. Drain. Eng. 141 (5), 04014068.
Ishii, K., et al., 2014. Big data analysis in medicine, agriculture and environmental sciences. Seibutsu-Kogaku Kaishi 92 (2), 92–93.
Jedermann, R., Borysov, M., Hartgenbusch, N., Jaeger, S., Sellwig, M., Lang, W., 2018. Testing lora for food applications-example application for airflow measurements inside cooled warehouses with apples. Procedia Manufacturing 24, 284–289.
Jensen, T., Apan, A., Zeller, L., 2009. Crop maturity mapping using a low-cost low-altitude remote sensing system. In: Proceedings of the 2009 Surveying and Spatial Sciences Institute Biennial International Conference (SSC 2009). Surveying and Spatial Sciences Institute, pp. 1231–1243.
Jhuria, M., Kumar, A., Borse, R., 2013. Image processing for smart farming: detection of disease and fruit grading. In: 2013 IEEE Second International Conference on Image Information Processing (ICIIP-2013). IEEE, pp. 521–526.
Jia, Y., Shelhamer, E., Donahue, J., Karayev, S., Long, J., Girshick, R., Guadarrama, S., Darrell, T., 2014. Caffe: Convolutional architecture for fast feature embedding. In: Proceedings of the 22nd ACM International Conference on Multimedia, pp. 675–678.
Jin, X., Kumar, L., Li, Z., Xu, X., Yang, G., Wang, J., 2016. Estimation of winter wheat biomass and yield by combining the aquacrop model and field hyperspectral data. Rem. Sens. 8 (12), 972.
Jordan, C.F., 1969. Derivation of leaf-area index from quality of light on the forest floor. Ecology 50 (4), 663–666.
Jordan, R., Eudoxie, G., Maharaj, K., Belfon, R., Bernard, M., 2016. Agrimaps: improving site-specific land management through mobile maps. Comput. Electron. Agric. 123, 292–296.
Kamilaris, A., Prenafeta-Boldú, F.X., 2018. Deep learning in agriculture: a survey. Comput. Electron. Agric. 147, 70–90.
Kamilaris, A., Gao, F., Prenafeta-Boldu, F.X., Ali, M.I., 2016. Agri-iot: A Semantic Framework for Internet of Things-Enabled Smart Farming Applications, pp. 442–447.
Kashyap, P.K., Kumar, S., Jaiswal, A., Prasad, M., Gandomi, A.H., 2021. Towards Precision Agriculture: IoT-enabled Intelligent Irrigation Systems Using Deep Learning Neural Network. IEEE Sensors Journal 1–11. https://doi.org/10.1109/JSEN.2021.3069266 vol: preprint.
Kaul, M., Hill, R.L., Walthall, C., 2005. Artificial neural networks for corn and soybean yield prediction. Agric. Syst. 85 (1), 1–18.
Kemp, K., et al., 2008. Encyclopedia of Geographic Information Science. Sage.
Kerkez, B., Glaser, S.D., Bales, R.C., Meadows, M.W., 2012. Design and performance of a wireless sensor network for catchment-scale snow and soil moisture measurements. Water Resour. Res. 48 (9).
Kim, Y., Evans, R.G., Iversen, W.M., 2008. Remote sensing and control of an irrigation system using a distributed wireless sensor network. IEEE transactions on instrumentation and measurement 57 (7), 1379–1387.
King, K.W., Williams, M.R., Fausey, N.R., 2015. Contributions of systematic tile drainage to watershed-scale phosphorus transport. J. Environ. Qual. 44 (2), 486–494.
Kisseleff, S., Akyildiz, I.F., Gerstacker, W.H., 2018. Survey on advances in magnetic induction-based wireless underground sensor networks. IEEE Internet of Things Journal 5 (6), 4843–4856.
Kitzes, J., Wackernagel, M., Loh, J., Peller, A., Goldfinger, S., Cheng, D., Tea, K., 2008. "Shrink and share: humanity's present and future ecological footprint. Phil. Trans. Biol. Sci. 363 (1491), 467–475.
Kozak, J.A., Aiken, R.M., Flerchinger, G.N., Nielsen, D.C., Ma, L., Ahuja, L., 2007. Comparison of modeling approaches to quantify residue architecture effects on soil temperature and water. Soil Tillage Res. 95 (1–2), 84–96.

Krizhevsky, A., Sutskever, I., Hinton, G.E., 2017. Imagenet classification with deep convolutional neural networks. Commun. ACM 60 (6), 84–90.

M. Kumhar and J. Bhatia, "Emerging Communication Technologies for 5g-Enabled Internet of Things Applications," *Blockchain For 5G-Enabled IoT*, p. 133.

Kuwata, K., Shibasaki, R., 2015. Estimating crop yields with deep learning and remotely sensed data,. In: 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). IEEE, pp. 858–861.

Lambert, D., 2000. M.; cooper, martha. c. Issues in supply chain management. Industrial Marketing Management 29, 65–83.

Langendoen, K., Baggio, A., Visser, O., 2006. Murphy loves potatoes: experiences from a pilot sensor network deployment in precision agriculture. In: Proceedings 20th IEEE International Parallel & Distributed Processing Symposium. IEEE, p. 8.

Lazzarini, S., Chaddad, F., Cook, M., 2001. Integrating supply chain and network analyses: the study of netchains. Journal on chain and network science 1 (1), 7–22.

Leaf monitor system. http://www.westernfarmpress.com/tree-nuts/uc- research-explores-continuous-leaf-monitor-system-maximize-irrigation-almonds.

LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. Nature 521 (7553), 436–444.

Leduc, G., Kubler, S., Georges, J.-P., 2021. Innovative blockchain-based farming marketplace and smart contract performance evaluation. J. Clean. Prod. 127055.

Lee, S.H., Chan, C.S., Wilkin, P., Remagnino, P., 2015. Deep-plant: plant identification with convolutional neural networks,. In: 2015 IEEE International Conference on Image Processing (ICIP). IEEE, pp. 452–456.

Lesser, A., 2014. Big data and big agriculture. Gigaom Research 11.

Li, S., Simonian, A., Chin, B.A., 2010. "Sensors for agriculture and the food industry," *Electrochemical Society Interface* 19 (4), 41.

Li, Z., Wang, J., Tang, H., Huang, C., Yang, F., Chen, B., Wang, X., Xin, X., Ge, Y., 2016. Predicting grassland leaf area index in the meadow steppes of northern China: a comparative study of regression approaches and hybrid geostatistical methods. Rem. Sens. 8 (8), 632.

Liang, L., Di, L., Zhang, L., Deng, M., Qin, Z., Zhao, S., Lin, H., 2015. Estimation of crop lai using hyperspectral vegetation indices and a hybrid inversion method. Rem. Sens. Environ. 165, 123–134.

Lin, J., Yu, W., Zhang, N., Yang, X., Zhang, H., Zhao, W., 2017a. A survey on internet of things: architecture, enabling technologies, security and privacy, and applications. IEEE Internet of Things Journal 4 (5), 1125–1142.

Lin, S.-C., Alshehri, A.A., Wang, P., Akyildiz, I.F., 2017b. Magnetic induction-based localization in randomly deployed wireless underground sensor networks. IEEE Internet of Things Journal 4 (5), 1454–1465.

Linke, M., Beuche, H., Geyer, M., Hellebrand, H.J., et al., 2000. Possibilities and limits of the use of thermography for the examination of horticultural products. Agrartechnische Forschung 6 (6), 110–114.

Luus, F.P., Salmon, B.P., Van den Bergh, F., Maharaj, B.T.J., 2015. Multiview deep learning for land-use classification. Geosci. Rem. Sens. Lett. IEEE 12 (12), 2448–2452.

Machado, B.B., Orue, J.P., Arruda, M.S., Santos, C.V., Sarath, D.S., Goncalves, W.N., Silva, G.G., Pistori, H., Roel, A.R., Rodrigues Jr., J.F., 2016. Bioleaf: a professional mobile application to measure foliar damage caused by insect herbivory. Comput. Electron. Agric. 129, 44–55.

Magney, T.S., Eitel, J.U., Vierling, L.A., 2017. Mapping wheat nitrogen uptake from rapideye vegetation indices. Precis. Agric. 18 (4), 429–451.

Mahlein, A., 2016. Present and future trends in plant disease detection. Plant Dis. 100 (2), 1–11.

Mahlein, A.-K., Oerke, E.-C., Steiner, U., Dehne, H.-W., 2012. Recent advances in sensing plant diseases for precision crop protection. Eur. J. Plant Pathol. 133 (1), 197–209.

Manikanthan, S., et al., 2021. Implementation and design of wireless iot network using deep learning. Turkish Journal of Computer and Mathematics Education (TURCOMAT) 12 (3), 563–572.

Maresma, Á., Ariza, M., Martínez, E., Lloveras, J., Martínez-Casasnovas, J.A., 2016. Analysis of vegetation indices to determine nitrogen application and yield prediction in maize (zea mays l.) from a standard uav service. Rem. Sens. 8 (12), 973.

Mattikalli, N.M., Engman, E.T., Jackson, T.J., Ahuja, L.R., 1998. Microwave remote sensing of temporal variations of brightness temperature and near-surface soil water content during a watershed-scale field experiment, and its application to the estimation of soil physical properties. Water Resour. Res. 34 (9), 2289–2299.

Mehra, L.K., Cowger, C., Gross, K., Ojiambo, P.S., 2016. Predicting pre-planting risk of stagonospora nodorum blotch in winter wheat using machine learning models. Front. Plant Sci. 7, 390.

Minh, D.H.T., Ienco, D., Gaetano, R., Lalande, N., Ndikumana, E., Osman, F., Maurel, P., 2017. Deep Recurrent Neural Networks for Mapping Winter Vegetation Quality Coverage via Multi-Temporal Sar Sentinel-1 arXiv preprint arXiv:1708.03694.

Mishra, S., Mishra, D., Santra, G.H., 2016. Applications of machine learning techniques in agricultural crop production: a review paper. Indian J. Sci. Technol 9 (38), 1–14.

Mkhabela, M., Bullock, P., Raj, S., Wang, S., Yang, Y., 2011. Crop yield forecasting on the canadian prairies using modis ndvi data. Agric. For. Meteorol. 151 (3), 385–393.

Mohammadpoor, M., Torabi, F., 2018. Big Data Analytics in Oil and Gas Industry: an Emerging Trend. *Petroleum*.

Mohanty, S.P., Hughes, D.P., Salathé, M., 2016. Using deep learning for image-based plant disease detection. Front. Plant Sci. 7, 1419.

Muñoz-Huerta, R.F., Guevara-Gonzalez, R.G., Contreras-Medina, L.M., Torres-Pacheco, I., Prado-Olivarez, J., Ocampo-Velazquez, R.V., 2013. A review of methods for sensing the nitrogen status in plants: advantages, disadvantages and recent advances. Sensors 13 (8), 10 823–910 843.

Naz, B., Bowling, L., 2008. Automated identification of tile lines from remotely sensed data. Transactions of the ASABE 51 (6), 1937–1950.

Naz, B., Ale, S., Bowling, L., 2009. Detecting subsurface drainage systems and estimating drain spacing in intensively managed agricultural landscapes. Agric. Water Manag. 96 (4), 627–637.

Noyes, K., 2014. Big Data Poised to Change the Face of Agriculture. fortune data.

Orlando, F., Movedi, E., Coduto, D., Parisi, S., Brancadoro, L., Pagani, V., Guarneri, T., Confalonieri, R., 2016. Estimating leaf area index (lai) in vineyards using the pocketlai smart-app. Sensors 16 (12), 2004.

Osterwalder, A., 2004. The Business Model Ontology a Proposition in a Design Science Approach. Ph.D. dissertation. Université de Lausanne, Faculté des hautes études commerciales.

Palomino, W., Morales, G., Huamán, S., Telles, J., 2018. Petefa: Geographic information system for precision agriculture. In: 2018 IEEE XXV International Conference on Electronics, Electrical Engineering and Computing (INTERCON). IEEE, pp. 1–4.

Pan, S.J., Yang, Q., 2010. A survey on transfer learning. IEEE Trans. Knowl. Data Eng. 22 (10), 1345 vol. 1359.

Panda, S.S., Ames, D.P., Panigrahi, S., 2010. Application of vegetation indices for agricultural crop yield prediction using neural network techniques. Rem. Sens. 2 (3), 673–696.

Pantazi, X.E., Moshou, D., Alexandridis, T., Whetton, R.L., Mouazen, A.M., 2016. Wheat yield prediction using machine learning and advanced sensing techniques. Comput. Electron. Agric. 121, 57–65.

Papageorgiou, E.I., Markinos, A.T., Gemtos, T.A., 2011. Fuzzy cognitive map based approach for predicting yield in cotton crop production as a basis for decision support system in precision agriculture application. Appl. Soft Comput. 11 (4), 3643–3657.

Petäjäjärvi, J., Mikhaylov, K., Yasmin, R., Hämäläinen, M., Iinatti, J., 2017. Evaluation of lora lpwan technology for indoor remote health and wellbeing monitoring. Int. J. Wireless Inf. Network 24 (2), 153–165.

S. Pongnumkul, P. Chaovalit, and N. Surasvadi, "Applications of smartphone-based sensors in agriculture: a systematic review of research," Journal of Sensors, vol. 2015, 2015.

Popović, T., Latinović, N., Pešić, A., Zečević, Ž., Krstajić, B., Djukanović, S., 2017. Architecting an iot-enabled platform for precision agriculture and ecological monitoring: a case study. Comput. Electron. Agric. 140, 255–265.

Potter, K., Cruse, R., Horton, R., 1985. Tillage effects on soil thermal properties. Soil Sci. Soc. Am. J. 49 (4), 968–973.

Prakash, A., 2000. Thermal remote sensing: concepts, issues and applications. International Archives of Photogrammetry and Remote Sensing 33 (B1; PART 1), 239–243.

Prasad, S., Bruce, L.M., Chanussot, J., 2011. Optical Remote Sensing. Advances in Signal Processing and Exploitation Techniques.

Provan, K.G., Kenis, P., 2008. Modes of network governance: structure, management, and effectiveness. J. Publ. Adm. Res. Theor. 18 (2), 229–252.

Puig, E., Gonzalez, F., Hamilton, G., Grundy, P., 2015. Assessment of Crop Insect Damage Using Unmanned Aerial Systems: A Machine Learning Approach.

Purdue university's digital agriculture initiative. http://news.arubanetworks.com/press-release/purdue-universitys-digital-agriculture-initiative-advances-farming-and-food-production.

Quattrochi, D.A., Luvall, J.C., 1999. Thermal infrared remote sensing for analysis of landscape ecological processes: methods and applications. Landsc. Ecol. 14 (6), 577–598.

Rahnemoonfar, M., Sheppard, C., 2017. Deep count: fruit counting based on deep simulated learning. Sensors 17 (4), 905.

Rhoads, F.M., Yonts, C.D., 1991. Irrigation scheduling for corn-why and how. National Corn Handbook 20.

PASCAL VOC Project, 2012. The PASCAL Visual Object Classes. Obtenido de. http://host.robots.ox.ac.uk/pascal/VOC/.

Rojo, F., Kizer, E., Upadhyaya, S., Ozmen, S., Ko-Madden, C., Zhang, Q., 2016. A leaf monitoring system for continuous measurement of plant water status to assist in precision irrigation in grape and almond crops. IFAC-PapersOnLine 49 (16), 209–215.

Rouphael, Y., Spíchal, L., Panzarová, K., Casa, R., Colla, G., 2018. High-throughput plant phenotyping for developing novel biostimulants: from lab to field or from field to lab? Front. Plant Sci. 9, 1197.

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., Berg, A.C., Fei-Fei, L., dec 2015. ImageNet large scale visual recognition challenge. Int. J. Comput. Vis. 115 (3), 211–252.

Ruß, G., 2009. Data mining of agricultural yield data: a comparison of regression models. In: Industrial Conference on Data Mining. Springer, pp. 24–37.

Sa, I., Ge, Z., Dayoub, F., Upcroft, B., Perez, T., McCool, C., 2016. Deepfruits: A fruit detection system using deep neural networks. Sensors 16 (8), 1222.

Sakamoto, T., Gitelson, A.A., Arkebauer, T.J., 2013. Modis-based corn grain yield estimation model incorporating crop phenology information. Rem. Sens. Environ. 131, 215–231.

Satir, O., Berberoglu, S., 2016. Crop yield prediction under soil salinity using satellite derived vegetation indices. Field Crop. Res. 192, 134–143.

Schmidhuber, J., 2015. Deep learning in neural networks: an overview. Neural Network. 61, 85–117.

Scholz, M., 2018. "Enhancing adoption of integrated weed management–an australian farmer's perspective. Outlooks Pest Manag. 29 (2), 66–69.

Schuster, E.W., Kumar, S., Sarma, S.E., Willers, J.L., Milliken, G.A., 2011. Infrastructure for data-driven agriculture: identifying management zones for cotton using statistical modeling and machine learning techniques. In: 2011 8th International Conference & Expo on Emerging Technologies for a Smarter World. IEEE, pp. 1–6.

Sehgal, G., Gupta, B., Paneri, K., Singh, K., Sharma, G., Shroff, G., 2017. Crop planning using stochastic visual optimization. In: 2017 IEEE Visualization in Data Science (VDS). IEEE, pp. 47–51.
Sekulic, P., Djurovic, S., 2016. Detection of downey mildew in grapevine leaves using support vector machine. Proceedings of the 21st Information Technology IT 16, 169–172.
Sensor network for irrigation scheduling. http://soilphysics.okstate.edu/research/moisst/.
Shafian, S., Maas, S.J., 2015. Index of soil moisture using raw landsat image digital count data in Texas high plains. Rem. Sens. 7 (3), 2352–2372.
Shao, Y., Zhao, C., Bao, Y., He, Y., 2012. Quantification of nitrogen status in rice by least squares support vector machines and reflectance spectroscopy. Food Bioprocess Technol. 5 (1), 100–107.
Shi, X., An, X., Zhao, Q., Liu, H., Xia, L., Sun, X., Guo, Y., 2019. State-of-the-art internet of things in protected agriculture. Sensors 19 (8), 1833.
Shirish, P., Bhalerao, S.A., 2013. Precision farming: the most scientific and modern approach to sustainable agriculture. Int. Res. J. of Science & Engineering 1 (2), 21–30 [Online]. Available: www.irjse.
Singh, A., Ganapathysubramanian, B., Singh, A.K., Sarkar, S., 2016. Machine learning for high-throughput stress phenotyping in plants. Trends Plant Sci. 21 (2), 110–124.
Sisinni, E., Saifullah, A., Han, S., Jennehag, U., Gidlund, M., 2018. Industrial internet of things: challenges, opportunities, and directions. IEEE Transactions on Industrial Informatics 14 (11), 4724–4734.
Smith, D.R., King, K.W., Johnson, L., Francesconi, W., Richards, P., Baker, D., Sharpley, A.N., 2015. Surface runoff and tile drainage transport of phosphorus in the midwestern United States. J. Environ. Qual. 44 (2), 495–502.
Soliman, A., Heck, R.J., Brenning, A., Brown, R., Miller, S., 2013. Remote sensing of soil moisture in vineyards using airborne and ground-based thermal inertia data. Rem. Sens. 5 (8), 3729–3748.
Song, X., Zhang, G., Liu, F., Li, D., Zhao, Y., Yang, J., 2016. Modeling spatio-temporal distribution of soil moisture by deep learning-based cellular automata model. Journal of Arid Land 8 (5), 734–748.
Sonka, S., 2015. Big data: from hype to agricultural tool. Farm Policy Journal 12 (1), 1–9.
Sopegno, A., Calvo, A., Berruto, R., Busato, P., Bocthis, D., 2016. A web mobile application for agricultural machinery cost analysis. Comput. Electron. Agric. 130, 158–168.
Sørensen, R.A., Rasmussen, J., Nielsen, J., Jørgensen, R.N., 2017. Thistle detection using convolutional neural networks. In: 2017 EFITA WCCA CONGRESS, p. 161.
Stark, B., Smith, B., Chen, Y., 2014. Survey of thermal infrared remote sensing for unmanned aerial systems. In: 2014 International Conference on Unmanned Aircraft Systems (ICUAS). IEEE, pp. 1294–1299.
Stas, M., Van Orshoven, J., Dong, Q., Heremans, S., Zhang, B., 2016. A comparison of machine learning algorithms for regional wheat yield prediction using ndvi time series of spot-vgt. In: 2016 Fifth International Conference on Agro-Geoinformatics (Agro-Geoinformatics). IEEE, pp. 1–5.
Steen, K.A., Christiansen, P., Karstoft, H., Jørgensen, R.N., 2016. Using deep learning to challenge safety standard for highly autonomous machines in agriculture. Journal of Imaging 2 (1), 6.
Stoll, M., Schultz, H.R., Baecker, G., Berkelmann-Loehnertz, B., 2008. Early pathogen detection under different water status and the assessment of spray application in vineyards through the use of thermal imagery. Precis. Agric. 9 (6), 407–417.
Suen, R.C.L., Chang, K.T., Wan, M.P.-H., Ng, Y.C., Tan, B.C., 2014. Interactive experiences designed for agricultural communities. In: CHI'14 Extended Abstracts on Human Factors in Computing Systems, pp. 551–554.
Sullivan, D., Shaw, J., Mask, P., Rickman, D., Guertal, E., Luvall, J., Wersinger, J., 2004. Evaluation of multispectral data for rapid assessment of wheat straw residue cover. Soil Sci. Soc. Am. J. 68 (6), 2007–2013.
Sun, Z., Zheng, F., Yin, S., et al., 2013. Perspectives of research and application of big data on smart agriculture. J. Agric. Sci. Technol. 15 (6), 63–71.
Swain, K.C., Thomson, S.J., Jayasuriya, H.P., 2010. Adoption of an unmanned helicopter for low-altitude remote sensing to estimate yield and total biomass of a rice crop. Transactions of the ASABE 53 (1), 21–27.
Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., Rabinovich, A., 2015. Going deeper with convolutions. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1–9.
Szegedy, C., Ioffe, S., Vanhoucke, V., Alemi, A., 2017. Inception-v4, inception-resnet and the impact of residual connections on learning. 31st aaai. In: Conf Artif Intell AAAI, vol. 2017.
Szewczyk, R., Zieliński, C., Kaliczyńska, M., 2018. Automation 2018: Advances in Automation, Robotics and Measurement Techniques, vol. 743. Springer.
Tan, X., Sun, Z., Akyildiz, I.F., 2015. Wireless underground sensor networks: mi-based communication systems for underground applications. IEEE Antenn. Propag. Mag. 57 (4), 74–87.
Tang, L., Shao, G., 2015. Drone remote sensing for forestry research and practices. J. For. Res. 26 (4), 791–797.
Tellaeche, A., Burgos-Artizzu, X.P., Pajares, G., Ribeiro, A., 2008. A vision-based method for weeds identification through the bayesian decision theory. Pattern Recogn. 41 (2), 521–530.
Tiusanen, M.J., 2013. Soil scouts: description and performance of single hop wireless underground sensor nodes. Ad Hoc Netw. 11 (5), 1610–1618.
Tooker, J., Vuran, M.C., 2012. Mobile data harvesting in wireless underground sensor networks. In: 2012 9th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON). IEEE, pp. 560–568.
Torres-Sánchez, J., López-Granados, F., Serrano, N., Arquero, O., Peña, J.M., 2015. High-throughput 3-d monitoring of agricultural-tree plantations with unmanned aerial vehicle (uav) technology. PloS One 10 (6), e0130479.
Tremblay, N., Fallon, E., Ziadi, N., 2011. Sensing of crop nitrogen status: opportunities, tools, limitations, and supporting information requirements. HortTechnology 21 (3), 274–281.
Tripodi, P., Massa, D., Venezia, A., Cardi, T., 2018. Sensing technologies for precision phenotyping in vegetable crops: current status and future challenges. Agronomy 8 (4), 57.
R. Ullah, A. W. Abbas, M. Ullah, R. U. Khan, I. U. Khan, N. Aslam, and S. S. Aljameel, “Eewmp: an iot-based energy-efficient water management platform for smart irrigation,” Sci. Program., vol. 2021, 2021.
Van der Vorst, J., Beulens, A., van Beek, P., 2005. 10. innovations in logistics and ict in food supply chain networks. Innov. agri-food Syst 245.
Van Wittenberghe, S., Verrelst, J., Rivera, J.P., Alonso, L., Moreno, J., Samson, R., 2014. Gaussian processes retrieval of leaf parameters from a multi-species reflectance, absorbance and fluorescence dataset. J. Photochem. Photobiol. B Biol. 134, 37–48.
Vasisht, D., Kapetanovic, Z., Won, J., Jin, X., Chandra, R., Sinha, S., Kapoor, A., Sudarshan, M., Stratman, S., 2017. Farmbeats: An iot platform for data-driven agriculture. In: 14th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 17), pp. 515–529.
Venkatesan, R., Kathrine, G.J.W., Ramalakshmi, K., 2018. Internet of things based pest management using natural pesticides for small scale organic gardens. J. Comput. Theor. Nanosci. 15 (9–10), 2742–2747.
Verhoosel, J., van Bekkum, M., Verwaart, T., 2016. Horticube: a platform for transparent, trusted data sharing in the food supply chain. Proceedings in food system dynamics 384–388.
Vuran, M.C., Akyildiz, I.F., 2010. Channel model and analysis for wireless underground sensor networks in soil medium. Physical communication 3 (4), 245–254.
Vuran, M.C., Salam, A., Wong, R., Irmak, S., 2018. Internet of underground things in precision agriculture: architecture and technology aspects. Ad Hoc Netw. 81, 160–173.
Wang, D.-C., Zhang, G.-L., Zhao, M.-S., Pan, X.-Z., Zhao, Y.-G., Li, D.-C., Macmillan, B., 2015. Retrieval and mapping of soil texture based on land surface diurnal temperature range data from modis. PloS One 10 (6), e0129977.
Wark, T., Corke, P., Sikka, P., Klingbeil, L., Guo, Y., Crossman, C., Valencia, P., Swain, D., Bishop-Hurley, G., 2007. Transforming agriculture through pervasive wireless sensor networks. IEEE Pervasive Computing 6 (2), 50–57.
Waskom, R., Bauder, T., Pearson, R., 1995. Best Management Practices for Agricultural Pesticide Use. *Bulletin (Colorado State University. Extension); XCM-177*.
Weng, Q., 2009. Thermal infrared remote sensing for urban climate and environmental studies: methods, applications, and trends. ISPRS J. Photogrammetry Remote Sens. 64 (4), 335–344.
Wolfert, S., Ge, L., Verdouw, C., Bogaardt, M.-J., 2017a. “Big data in smart farming–a review. Agric. Syst. 153, 69–80.
Wolfert, S., Ge, L., Verdouw, C., Bogaardt, M.-J., 2017b. “Big data in smart farming–a review. Agric. Syst. 153, 69–80.
Wu, Q., Jin, Y., Bao, Y., Hai, Q., Yan, R., Chen, B., Zhang, H., Zhang, B., Li, Z., Li, X., et al., 2015. Comparison of two inversion methods for leaf area index using hj-1 satellite data in a temperate meadow steppe. Int. J. Rem. Sens. 36 (19–20), 5192–5207.
Yalcin, H., 2017. Plant Phenology Recognition Using Deep Learning: Deep-Pheno. In: 2017 6th International Conference on Agro-Geoinformatics. IEEE, pp. 1–5.
Yan-e, D., 2011. Design of intelligent agriculture management information system based on iot. In: 2011 Fourth International Conference on Intelligent Computation Technology and Automation, vol. 1. IEEE, pp. 1045–1049.
Yanru, Z., Xiaohong, W., 1998. Using airborne thermal infrared remote sensing techniques to detect underground oil pipelines. Remote Sensing for Land & Resources 10 (3), 86–89.
Ye, Y., Hao, L., Liu, M., Wu, H., Zhang, X., Zhao, Z., 2016. Design of farmland environment remote monitoring system based on zigbee wireless sensor network. In: Frontier Computing. Springer, pp. 405–416.
Yu, Q., Shi, Y., Tang, H., Yang, P., Xie, A., Liu, B., Wu, W., 2017. efarm: a tool for better observing agricultural land systems. Sensors 17 (3), 453.
Zhang, D., 2006. Advances in Machine Learning Applications in Software Engineering. Igi Global.
Zhang, N., Wang, M., Wang, N., 2002. “Precision agriculture—a worldwide overview. Comput. Electron. Agric. 36 (2–3), 113–132.
Zhang, L., Zhang, J., Kyei-Boahen, S., Zhang, M., et al., 2010. Simulation and prediction of soybean growth and development under field conditions. Am-Euras J Agr Environ Sci 7 (4), 374–385.
Zhang, X., Andreyev, A., Zumpf, C., Negri, M.C., Guha, S., Ghosh, M., 2017. Thoreau: A subterranean wireless sensing network for agriculture and the environment. In: 2017 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS). IEEE, pp. 78–84.
Zhang, L., Dabipi, I.K., Brown Jr., W.L., 2018. Internet of Things Applications for Agriculture. Internet of Things A to Z: Technologies and Applications, pp. 507–528.
Zhao, Y., Gong, L., Huang, Y., Liu, C., 2016. A review of key techniques of vision-based control for harvesting robot. Comput. Electron. Agric. 127, 311–323.
Zhu, N., Xia, Y., Liu, Y., Zang, C., Deng, H., Ma, Z., 2018. Temperature and humidity monitoring system for bulk grain container based on lora wireless technology. In: International Conference on Cloud Computing and Security. Springer, pp. 102–110.
Zujevs, A., Osadcuks, V., Ahrendt, P., 2015. Trends in robotic sensor technologies for fruit harvesting: 2010-2015. Procedia Computer Science 77, 227–233.
Zulkifli, C., Noor, N., 2017. Wireless sensor network and internet of things (iot) solution in agriculture. Pertanika Journal of Science & Technology 25 (1).

EPFL, plant village datase [Online]. Available: https://plantvillage.psu.edu/en/crops.
Loriot. the LoRaWAN® network server provider [Online]. Available: https://www.loriot.io/.
Analog and mixed-signal semiconductors — semtech: internet of things, data centers and mobility [Online]. Available: https://www.semtech.com/.
Best drones for agriculture 2020: the ultimate buyer's guide [Online]. Available: https://bestdroneforthejob.com/drone-buying-guides/agriculture-drone-buyers-guide/.
Case studies corporate landing page — IBM [Online]. Available: https://www.ibm.com/case-studies/search?search.
Chee seng chan - plant dataset [Online]. Available: http://web.fsktm.um.edu.my/$/sim$cschan/downloads_MKLeaf_dataset.html.
Cropx technologies welcome to the era of data driven farming [Online]. Available: https://www.cropx.com/.
Data Africa soil information service [Online]. Available: http://africasoils.net/services/data/.
Devicelynk industrial software solutions [Online]. Available: https://industrial-software.com/.
Digital agriculture cornell university agricultural experiment station [Online]. Available: https://cuaes.cals.cornell.edu/digital-agriculture/.
Digitalise your farming with 365FarmNet [Online]. Available: https://www.365farmnet.com/en/.
Enabling the Smart Agriculture Revolution - the Future of Farming through the IoT Perspective, 2016. Beecham Research.
Flavia, A leaf recognition algorithm for plant classification using PNN [Online]. Available: http://flavia.sourceforge.net/.
HereLab drip line psi and rain ,Soil moisture [Online]. Available: https://www.herelab.io/.
Image-Net Dataset images of different plants, trees, flowers or vegetables [Online]. Available: http://flavia.sourceforge.net/.
Internet of agriculture BioSense [Online]. Available: https://biosens.rs/?page_id=12564&lang=en.
Irrometer reading tools [Online]. Available: https://www.irrometer.com/loggers.html.
John Deere US products services information [Online]. Available: https://www.deere.com/en/.
Leafsnap dataset leafsnap an electronic field guide [Online]. Available: http://leafsnap.com/dataset/.
Libelium » connecting sensors to the cloud — powering the IoT revolution [Online]. Available: https://www.libelium.com/.
UC merced land use dataset [Online]. Available: http://weegee.vision.ucmerced.edu/datasets/landuse.html.
MimosaTEK – elevating traditional farming experience on the internet of things (IoT) platform [Online]. Available: https://mimosatek.com/en/.
FAO, 2009. How to Feed the World in 2050. Food and Agriculture Organization of the United Nations, Rome.
Plant task — ImageCLEF/LifeCLEF - multimedia retrieval in CLEF [Online]. Available: https://www.imageclef.org/2014/lifeclef/plant.
Precisionkawks:Agriculture: drone mapping and analytics [Online]. Available: https://www.precisionhawk.com/agriculture.
SapIP IRT infrared leaf temperature - dynamax [Online]. Available: https://dynamax.com/products/leaf-canopy-and-image-analysis/sapip-irt-infrared-leaf-temperature.
Senet: cloud-based software and services for the on-demand build-out and management of global IoT networks [Online]. Available: https://www.senetco.com/.
Smart Ag products - zenseio [Online]. Available: https://zenseio.com/smart-ag-products.
Smartrek - SPIDERMESH, Simple wireless solutions for a complex and fast changing world [Online]. Available: https://www.smartrek.io/.
Symphony link - internet of things wireless LPWA [Online]. Available: https://www.link-labs.com/symphony.
Syngenta Crop Challenge 2017: corn hybrids in 2,122 locations during the period from 2008 to 2016, along with weather and soil data [Online]. Available: http://host.robots.ox.ac.uk/pascal/VOC/.
Telit IoT solutions provider - modules, IoT platforms & IoT connectivity [Online]. Available: https://www.telit.com/.
TempuTech : technology driven company that provides scalable hardware and software solutions, whether it is a small farm with local bins or large elevator and dryer facilities [Online]. Available. http://www.temputech.com/.
The PASCAL visual object classes homepage [Online]. Available: http://host.robots.ox.ac.uk/pascal/VOC/.
Tule goodbye, pressure chamber [Online]. Available: https://www.tuletechnologies.com/.
U of A CES herbicide injury photo database [Online]. Available: https://plants.uaex.edu/herbicide/.
University of Bonn Photogrammetry, IGG :Sugar beets data set for positioning and visualization, for plant classification [Online]. Available: http://weegee.vision.ucmerced.edu/datasets/landuse.html.
AGI SureTrack IntelliFarms biological BinManager [Online]. Available: http://www.intellifarms.com.
Ice, Snow, 2020. And Glaciers and the Water Cycle. Water.Usgs.Gov. https://water.usgs.gov/edu/watercycleice.html.
What Percent of Earth Is Water?, 2020. Phys.Org. https://phys.org/news/2014-12-percent-earth.html.
20L sprinkler drone for orchard JT20L 606. http://www.wecanie.com/html/sprayer/products/.
Best drones for agriculture 2019: the ultimate buyer's guide. https://bestdroneforthejob.com/drone-buying-guides/.
Cloud computing helps agriculture industry grow cloud computing news. Cloud computing news. https://www.ibm.com/blogs/cloud-computing/2015/01/23/cloud-computing-helps-agriculture-industry-grow/.
Drone reforestation. Quicker Safer. Ready. https://www.droneseed.co/.
Fujitsu Launches New "Akisai" Cloud for the Food and Agricultural Industries".
AGRAS MG 1. https://www.dji.com/mg-1.
Harvesting the agricultural potential of drones. https://www.sanfordjournal.org/sjpp/2017.
PrecisionHawk. https://www.precisionhawk.com/drones.
Questuav Datahawk agriculture drone. Questuav Ltd. https://www.questuav.com/drones/datahawk-agriculture/.
These tree-planting drones are about to start an entire forest from the sky. https://www.fastcompany.com/40450262/.
A fully autonomous drone for daily scouting. https://www.agweb.com/article/a-fully-autonomous-drone-for-daily-scouting/.

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