A comprehensive review of internet of things and cutting-edge technologies empowering smart farming

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The agricultural sector plays an important role in contributing significantly to the gross domestic product (GDP) growth in developing countries. On the other hand, agriculture is widely affected by major factors such as environmental changes, natural disasters, pesticide control, and soil and irrigation-related issues, which reduce crop yield. The convergence of Industry 4.0 and agriculture offers an opportunity to move into the next generation of Agriculture 4.0. The internet of things (IoT), remote sensing, machine learning, deep learning, big data, cloud computing, thermal imaging, end-user apps and unmanned aerial vehicles offer a full-stack solution. IoT provides the ubiquitous connectivity of smart devices to the internet to collect, process and analyse a large amount of agriculture field data more quickly and synthesize them to make smart decisions using various machine learning and deep learning algorithms. This study reviews the challenges and major issues in the IoT agriculture domain and explores its emergence with new technologies. It covers the existing literature and illustrates how IoT application-based precision agriculture solutions have contributed. A case study on weed detection for smart agriculture using the YOLOv5 model is presented, achieving high accuracy. Finally, various IoT agriculture use cases are discussed, along with current research issues and possible solutions for future IoT-based agriculture advancement.

Keywords: Cutting-edge technologies, internet of things, precision farming, smart agriculture, weed detection.

AGRICULTURE is one of the major sectors to fulfill the demand for food across the world. It plays an important role in contributing significantly to gross domestic product (GDP) growth in developing countries. The agricultural sector in India engages a significant portion of the population, with 70% depending primarily on it for their livelihoods[1]. Based on specific facts and statistics, many Indian states have implemented an intra-state agriculture cluster development programme to double farmers' income by the year 2022 (ref. 2). Agriculture has undergone significant changes in the previous several decades in terms of its methods and use of contemporary strategies together with cutting-edge technology. However, conventional farming methods are region-centric in many nations. All farmers in a region cultivate the same general set of crops according to the same practices for sowing, nurturing, watering and harvesting times. These actions lead to unpredictability, excessive resource utilization and unchecked waste creation. Some of the challenges faced by the agricultural sector are: (i) lack of sufficient knowledge and standard practices of the latest framing trends. (ii) For the timely operation of crops, labour shortage and high labour charges are the main problems. (iii) Deficiency of soil nutrients occurs due to the same crop pattern followed after each harvest in a certain area-centric approach. (iv) Overuse of fertilizers, insecticides and pesticides with premature or delayed treatment of crops in traditional farming techniques. (v) Crop yield degradation due to depletion of the topsoil layer, environmental changes and unpredictable atmospheric effects. Numerous studies have focused on addressing the challenges that the agriculture industry faces in the realm of internet of things (IoT)[2]. The collection and analysis of data, coupled with the development of specialized smart solutions, will be crucial to the future of agriculture. State-of-the-art IoT technology properly plans limited resources and optimizes IoT to increase productivity and reduce costs[3]. Crop productivity is influenced by many factors, including environmental monitoring, field management, soil and crop monitoring, movement of an unwanted object, wildlife attacks, theft, etc.[4,5]. It can be managed by proper data collection through various sensors deployed in space, ground and underground for precision agriculture in a spatial and temporal manner for quick decision-making.

The agricultural industry will undergo another transformation through the fourth agricultural revolution, which will be driven by industry 4.0 (ref. 6). In order to assist farmers by predicting the strategy of enhancing agricultural yield, the agriculture system is offered as an idea of IoT, wireless sensor network (WSN) and cloud computing[7]. Agriculture divides huge fields into zones, and instead of administering irrigation, fertilizer, seeds and other farm inputs

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uniformly as in the past, each zone now receives individualized management inputs based on its specific location, soil type and management history[8]. Remote sensing (RS), IoT, machine learning (ML), deep learning (DL), big data, cloud computing, thermal imaging, end-user applications and unmanned aerial vehicles (UAVs) are just a few of the cutting-edge technologies that make up the full-stack system of Agriculture 4.0. The IoT-enabled 5G connectivity trend includes high data rates, better coverage and higher output, and thus provides solutions for agribusiness models to makes IoT work on actuators and drone devices[9]. For accurate statistics, a variety of sensors are used to measure the soil condition, field environment and health of the plants[10]. For the most part, wireless mesh networks and low-power wide area networks are used for data transfer while reporting the data produced during agricultural output[11]. Crop identification, yield forecasting and large-scale field monitoring have been expertly carried out using RS technologies[12]. Modern imaging and database analysis technology, which offers excellent prospects for real-time insights into agriculture, delivers analytical statistics for crop growth and disease pattern identification using ML and DL[8,13]. The current research trends in IoT agriculture include network- and infrastructure-oriented platforms, architecture, applications, security and challenges among others[14,15]. To ensure large-scale high-throughput and WSN use in rural regions, more network capacity and delivery latency reduction are required to increase agricultural productivity[16]. In order to obtain the full benefits of IoT, its implementation must include reliable connectivity, a security-based framework in agriculture business process development with the goal of increasing end-user satisfaction, improving operational excellence and generating revenue streams using agriculture IoT[17].

Figure 1 represents the generic IoT architecture in the context of smart agriculture. Four essential phases in a smart agricultural setting make up the main objective of the overall framework: data sensing, data collection, data transmission and data processing[8]. The structure of the framework is based on a multi-layer architecture consisting of five main layers: physical layer, network layer, middleware layer, service layer and application layer. The physical layer consists of various kinds of devices such as sensors, agriculture robots, UAVs, barcodes, GPS, RFID chips, actuators and other physical objects connected to perform sensing and control actions in the network of agriculture IoT[18]. At this level, with low processing capability and limited resources, sensors perform multiple tasks of data collection related to equipment positioning, motion detection, soil sensing, temperature and other environmental parameters, while action will be performed by the actuators and controllers based on the direction of the micro-controller unit. The network layer consists of a topology for data transmission via sink nodes from the physical layer to the middleware layer. Various communication modes, wired/wireless mediums with NFC, Bluetooth, Wi–Fi, 4G/5G, etc. are used for the transmission of information in IoT[9]. IoT also uses a wide range of wireless access technologies (e.g. Wi–Fi, Bluetooth, ZWave, ZigBee, long-range wide-area networks (LoRaWAN), SigFox) and mobile technologies (e.g. GPRS/2G or eMTC and NBIoT) and Ethernet for data transmission. The hardware and software complexities are encapsulated by the middleware layer to make it easier to use and develop IoT apps and services[18]. It is responsible for managing the results achieved and making decisions based on information received from the network layer for ubiquitous computing. It also handles data transfer, data aggregation, protocol conversion, heterogeneous network management, security and settings for information acquisition. HYDRA and SMEPP are highly effective middleware solutions in the agricultural setting due to their context-aware functionalities[2]. The service layer provides several technologies, such as network management services like SDN/NFV, cloud and fog computing, AI/ML/DL and big data analytics for the application layer[19]. This layer focuses on specific areas or domains, such as monitoring, detection, control, decision-making, recognition, etc. This approach streamlines the process of performing tasks such as sensing and actuation. A variety of IoT-based messaging protocols are used by the application layer to carry out a variety of agricultural tasks, which include some well-known

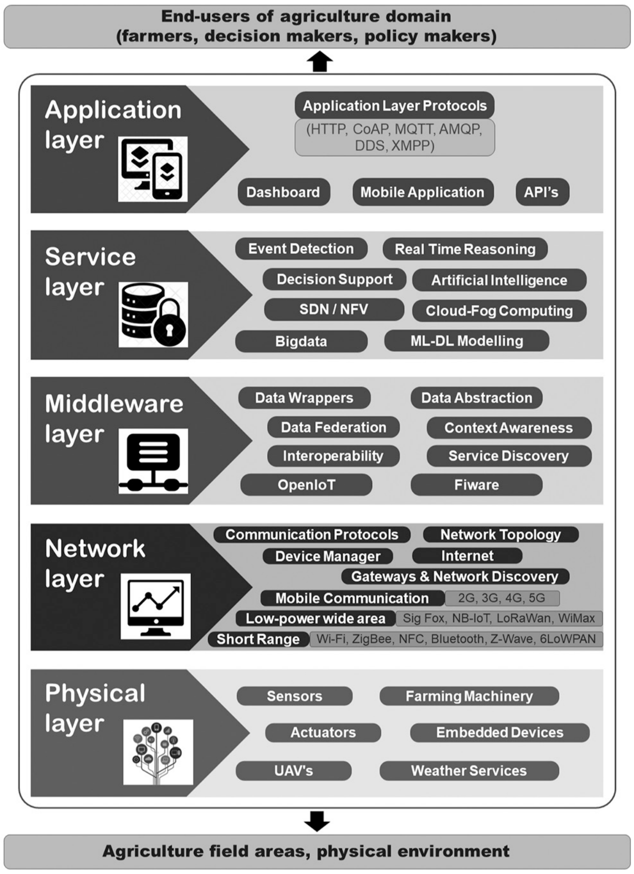

Figure 1. Layered architecture of agriculture internet of things.

protocols such as MQTT, CoAP, XMPP, AMQP, etc.[20]. This layer should improve RESTful APIs to make it easier to share and use information by searching and retrieving real-time information to discover the potential benefits of IoT in agriculture.

Agriculture 4.0 brings in more productive farming practices with intelligent monitoring and decision-making systems. Since the advent of wireless sensor technology two decades ago, IoT-based smart farming has been actively under development. Farooq *et al.*[3] addressed the physical, data acquisition, processing and analytics components of IoT-based smart farming, as well as the network architecture, layers and topologies that were utilized. Elijah *et al.*[21] discussed the application of IoT and data analytics technology in agriculture. Specifically, they addressed issues such as security and fraud prevention, cost reduction and operational efficiency within the Agi-IoT ecosystem. Alharbi and Aldossary[22] explored the integrated strategy involving edge, fog and cloud architecture for overseeing resource needs in diverse agricultural tasks, aiming to improve the energy efficiency of smart farming systems. Ayaz *et al.*[23] discussed various wired/wireless sensors, UAVs and sensors for soil sampling, crop surveillance, crop yield forecasting and harvesting. Big data, AI and the IoT, were discussed in relation to agriculture by Misra *et al.*[24]. The use of UAVs in agriculture, greenhouse monitoring[25], disease detection[26], supply chain modernization, social media in the food sector, food quality evaluation and modernization for food traceability were covered in preliminary[27,28]. By examining agricultural application scenarios and practical tests, Feng *et al.*[29] examined wireless communication technologies for precision agriculture, particularly NBIoT, LoRa and ZigBee. Crop yield improvement[30], crop disease identification, weed detection[31] and pest detection[32] have all been actively explored using the applications of ML and DL. Zeynep *et al.*[33] performed a comprehensive literature review on the use of various DL approaches in smart agriculture. By fusing the ideas of IoT, cloud computing and data mining, Liu *et al.*[34] suggested an integrated framework for agriculture. In their study of IoT, AI and DL use cases, Qazi *et al.*[25] introduced a DL system based on convolutional neural networks for detecting and categorizing plant diseases, and the system was trained using annotated images of diseased plants.

For IoT-based agriculture, Friha *et al.*[18] discussed cloud computing, edge computing, SDN and NFV technologies and open-source middleware platforms. Misra *et al.*[24] explained the role of IoT and big data analysis for drone-based crop assessment, intelligent farm equipment, greenhouse monitoring and social media sentiment analysis for food assessment with Blockchain-based digital traceability were also included in their review. Chen *et al.*[10] designed an IoT-based 'AgriTalk' solution for precision-based soil farming, which was deployed on turmeric plants to enhance their growth and production. Jani and Chaubey[20] proposed a smart agriculture framework to automate and optimize resource utilization (irrigation, pest control and fertigation) in smart agriculture systems using IoT. Shafi *et al.*[19] presented an integrated approach for crop health assessment using IoT and drone based multi-spectral data for crop health with practical implementation. They collected data using IoT Agri node and DJI Phantom 4 Multi-spectral drone. Data classification task was carried out using SVM, NB and NN-based ML/DL algorithms. The integrated solution developed and implemented by Bouali *et al.*[26] provides smart irrigation that is cost-effective through real-time data collection and monitoring using a cloud-based IoT. For the experimental setup, the Arduino nano board was used with Zigbee communication technology for data acquisition, and the testbed was deployed using Raspberry Pi and Node-RED programming tools. Ferrag *et al.*[27] introduced security and privacy solutions for IoT applications in a four-tier architecture designed for IoT-based agriculture and classified potential threat models. Vangala *et al.*[28] examined several functional criteria necessary for the security protocols and generalized blockchain-based architecture with their consensus algorithms that may be used for the smart agriculture environment. Table 1 summarizes the advantages, limitations and key contributions made by different authors in the agriculture domain.

Sensors for Agriculture 4.0

In order to perceive factors like soil conditions, weather parameters, humidity, crop conditions, minerals, water level, pH values, etc. agriculturalists typically utilize sensors. In general, sensors can be classified into various types based on the properties of data captured, such as light intensity and reflection, electrode sensitivity, pressure and force values. Some common types of sensors include optical sensors, mechanical sensors, electrochemical sensors, dielectric sensors, position sensors and electronic sensors. Sensitivity of the sensor is the ratio of its output signal to its measured property. Various kinds of sensors and their utilization for agriculture applications are discussed below.

Soil temperature and moisture sensors

The soil moisture sensor measures the moisture and root water retention status of crops[3]. By detecting the dielectric constant of the soil, it may determine the volume of soil moisture. Also, soil temperature sensors are used to determine the water tension of the soil, profile depth, soil moisture and temperature. It comes in a variety of forms, including thermocouples, thermistors, resistance temperature detectors, infrared sensors and semiconductor sensors[18].

Meteorological station

It is a portable weather station that offers real-time weather updates on the following factors: air temperature, speed

Table 1. Analysis of various papers in the domain of smart agriculture based on the present study

Authors	Key aspects	Contribution	Methodology	Scope for improvement
Shafi *et al.*[19]	Hybrid approach for crop health identification using IoT, UAV and ML model.	Implementation of an integrated IoT and drone based multispectral data approach for crop health monitoring.	Data collection using IoT Agrinode + DJI Phantom4 multispectral Drone. Data classification using SVM, NB and NN-based ML/DL algorithm, NDVI maps, IoT sensor data maps.	Limited approach of ML/DL algorithms for classification. Reference dataset needed.
Jani *et al.*[20]	Resource optimization model using SMAIoT-smart agriculture system using IoT.	Simulating crop cycles with six irrigation modes: no irrigation, flooding, drip irrigation, sprinkler, soil water deficit and SMAIoT-auto. Specified automation in crop production stages (irrigation, fertigation, pest management).	Irrigation recommendation flow chart designed for a crop cycle. SMAIoT framework with event handling and processing, database operations, cloud services, communication topology, decision making and AI.	ML algorithms not specified for zone wise irrigation. The theoretical approach given only for pest control, fertigation, crop yield estimation.
Farooq *et al.*[3]	Analysis on smart farming implementation using IoT.	Layers of IoT based smart farming covered (perception, communication, data processing, data analytics). Explained architecture of communication, layers, topologies configuration and protocols.	Comparative study on existing wireless protocols, smartphone-based applications, industry related trends and security alert scenarios presented.	Theoretical aspects covered related to enabling technology. Limited discussion on ML/DL, edge/fog computing methods and uniform policy for IoT.
Elijah *et al.*[21]	Introduction of IoT and data analytics in agriculture.	Combined approach of IoT and Data Analytics presented. Highlighted use of IoT-based integrated farming, safety and fraud prevention, cost reduction and operational efficiency.	IoT and DA used for prediction, storage management and decision-making. Communication focused on LPWA technologies (NB-IoT).	NB IoT not explained in detail. Data analytics related technical specification and algorithm missing.
Alharbi *et al.*[22]	Energy efficient smart agriculture environment using edge/fog and cloud architecture.	Integrated paradigm deployed using Edge/Fog and cloud to improve energy-efficiency and reduce carbon emissions. Architecture allows real-time operation in several layers.	Studied the energy efficiency of IoT agriculture applications over an edge-cloud architecture, use the MILP optimization model.	Real-time implementation not done to evaluate the proposed model. Scope of ML/DL model integration to architecture for efficiency enhancement.
Friha *et al.*[18]	Review on IoT and emerging technologies for smart farming.	Presented layered IoT-based architecture of agriculture. Includes UAV, wireless technologies, cloud/edge solution, open-source IoT platforms and SDN-NFV approach.	Compared middleware platform and open-source IoT platforms to evaluate real-world smart farming that makes use of multiple emerging technologies.	Technical challenges need to minimize while IoT agriculture integrates with emerging technologies.
Ayaz *et al.*[23]	IoT-based smart agriculture fields.	Highlighted the role of technology and the hierarchy of IoT apps, sensor types and services for smart agriculture.	Presented wireless sensors, UAVs, cloud-computing, communication technologies and future vision of technical companies for Agri-IoT.	Limited coverage on ML/DL, Edge/Fog computing technology. Not included Security and privacy issues in the survey.
Misra *et al.*[24]	Review on AI, IoT and bigdata driven agriculture and food sector.	Discussed the use of IoT, AI and big data in agriculture, supply chain automation, and food quality evaluation in the context of future agri-food systems.	IoT and big data analysis for crop imaging using drones, intelligent agricultural equipment and monitoring greenhouses. Sentiment analysis based on social media, spectral techniques and sensor fusion for food evaluation with digital traceability based on a blockchain.	Comparative analysis for AI and ML-based algorithms is required. Security, interoperability related issues not covered.

and direction of the wind, relative humidity, radiation, solar intensity summary, rain gauge, evapotranspiration calculation and dew point calculation. This information can be used to monitor weather conditions during various agricultural operations. It is operated based on solar energy for remote area deployment, and different types of multiple sensors are mounted on this single unit.

NPK and pH sensors

They help to collect soil chemical data by measuring available chemical substances and pH levels to identify crop suitability in particular farm areas. They detect the activity of specific ions, such as nitrate, phosphate and potassium. Also, the pH values are determined, such as 6.5 to 7.5 (neutral), over 7.5 (alkaline) and less than 6.5 (acidic) using electrochemical sensors.

Meters, level and pressure sensors

It is crucial to continuously monitor and measure the water supply rate, as well as the dissolution rate of nutrients and minerals specific to crops. This involves monitoring values from the flow meter, level sensor and pressure sensors to control the activation or deactivation of irrigation valves, pumps and other related equipment[20]. The level sensor can be capacitance, optical, or conductivity. Float switch-based sensors are used for point-level indication, while ultrasonic and microwave-based sensors are for measuring continuous levels.

Infrared sensors

The measurement of environmental changes is achieved by generating infrared rays through two distinct methods, employing active or passive sensor types. An active IR sensor is a light-emitting diode and a receiver that emits and detects IR radiation. The passive IR sensors have only an LED and can only detect radiation[2]. In the field, infrared sensors can be deployed for object detection, tracking, plant counting, intrusion identification, etc.

RGB and multi-spectral camera

This is employed to examine agriculture crop statistics using NDVI and NDRE data through the effect of different wavelength bands of capture images via drones or RS field survey[19]. RGB cameras only record information for the red, green and blue bands of the electromagnetic spectrum, while multispectral cameras include additional bands. It used shortwave infrared, near-infrared, or thermal infrared bands to obtain additional information such as timely estimates of crop yield, pest and disease-infected areas and water-scarce areas.

GPS module

The global positioning system (GPS) is a technology used to determine the location of a device in the field of precision farming and digital agriculture. The precise location of machinery, weed patches, seed-planting ratios, yield maps, soil sampling, crop counting, and crop variability can all be determined using GPS.

Communication technology for Agriculture 4.0

For agricultural IoT applications to effectively serve rural areas, a vast coverage area and minimal deployment or maintenance costs are essential. 6LoWPAN, LoRa, IEEE 802.15.4, WiFi and Bluetooth are popular communication technologies used in agriculture IoT. It can be divided into standards for short-range and long-range communication. 5G is particularly well suited for most current deployments[35]. IoT utilizes a variety of wireless access technologies, including NFC, Bluetooth, ZWave, ZigBee and RFID, to cover short distances within 100 m and long distances up to 10 km using LoRaWAN, Sigfox and NB-IoT[36,37]. There are numerous wireless communication standards now in use for agricultural applications, some of which are mentioned below.

IEEE 802.11 Wi–Fi

A networking technique called Wireless Fidelity (Wi–Fi) enables sensor and IoT devices to connect over a wireless signal[38]. The communication range is covered from 20 m to 100 m (ref. 39). IEEE 802.11 is a wireless communication standard used for local area networks (WLAN) and is classified into various standards such as 802.11a, 802.11b, 802.11g, 802.11n and 802.11ac. These operate at different frequencies such as 5, 2.2, 2.4, 2.4/5, 60 and 5 GHz. These standards support data transfer between 1 Mb/s and 7 Gb/s.

6LowPAN and CoAP

Similar to IEEE 802.15.4, resource-constrained devices that interact via low-power, lossy networks widely adopt the 6LowPAN, which is an IPv6 adaption layer protocol[40]. Among other functions, 6LowPAN uses techniques for packet compression, fragmentation and reassembly to shrink IP datagrams and eliminate the majority of unnecessary fields[41]. At the application layer, CoAP is a RESTful protocol that sits on top of the UDP transport protocol. CoAP works like HTTP and can be converted to the latter for integration with web services, providing HTTP direct mapping capabilities, low processing overhead, simple proxy configuration and processing and support for asynchronous messaging[42].

LoRaWAN

The open and nonprofit organization Lora TM Alliance developed the long-range communication standard known as LoRaWAN. The two frequency bands used by LoRa modules are 433 and 868 MHz (ref. 19). The primary goal of this protocol is to provide compatibility across various operators[43]. Compared to other standards, the LoRa technology is better for communication in agricultural lands due to a clear line of sight. In order to increase agricultural output and foresee potential issues, a framework based on LoRa has been developed[44].

ZigBee

It is a wireless network protocol for low power that builds on the IEEE 802.15.4 standard[45]. With a working range of up to 100 m and a bandwidth of 250 kbps, ZigBee can operate in either a star topology, in which case the end devices are connected to the coordinator directly, or a tree topology using intermediate routers[42]. It can be widely used in agriculture environments where IoT sensors collect and transmit data to the remote server to be quickly analysed for decisions-making[46].

Mobile communication

Farmers can monitor agricultural production, soil and climatic conditions and detect real-time and temporal variability across fields using mobile communication[29]. Standards for mobile communications include multiple generations (2G/3G/4G/5G) with technology advancement. The 5G technology, with its wireless capabilities such as Massive MIMO, multiple access, ultra-dense network, multi-carrier and modulation and coding, can greatly facilitate the deployment of IoT devices. In addition, 5G includes network slicing, control-plane/user-plane separation, mobile edge computing and network function virtualization, among other innovations[47]. The 5G integrates IPv4 and IPv6, offering speeds between 10 and 800 Gbps.

WiMAX

This technology provides broadband multi-access connectivity, both wired and wireless, which supports portable, fixed and mobile communication. The data transmission range for global interoperability of microwave access is between 1.5 Mb/s and 1 Gb/s. However advancements in technology have improved the data transfer rate[48].

SigFox

This cellular network is designed for IoT and machine-to-machine (M2M) communications, characterized by a low data rate and an ultra-narrow band wireless technology[49]. In agriculture to locate the position of objects, a geolocation system can be built using the SigFox network with ultra-narrowband communication.

Bluetooth

The core specification version 4.0 introduced BLE, which is a low-energy and IoT-focused version[50]. The BLE network comprises two types of devices – Slaves and Masters. These slaves and masters are linked together in a star topology. BLE uses 40 channels with a 2 MHz spacing and runs in the unlicensed 2.4 GHz ISM band[51]. The coverage area typically spans many tens of m, and the physical layer data throughput is 1 Mb/s. Many IoT agricultural equipment offer Bluetooth for multi-tier agricultural applications to support a close communication range[52].

NB-IoT

LPWA-based communication technologies, such as the Narrowband Internet of Things (NB-IoT), are highly suitable for the agriculture industry. NB-IoT, a 3GPP standard cellular technology, has several promising features, including long-distance coverage, low device power consumption, ultra-low device cost, simplified implementation and support for a large number of devices with low throughput[53,54]. Its wide geographical coverage, scalability, low cost and long battery life of up to 10 years meet the significant needs of the IoT-based agriculture domain[55].

MQTT

This Message Queue Telemetry Transport protocol is well suited for IoT networks because it is a lightweight protocol that works on the publish/subscribe approach for messaging. MQTT comprises four primary components like subscribers, publishers, brokers and messages for facilitating communication. In MQTT, session awareness features are provided by the use of TCP at the transport layer, but device-to-device communication and multicast are not supported[56].

Enabling technologies and their role in Agriculture 4.0

From the perspective of intelligent agriculture using IoT, it includes not only sensors and communication networks, but also various technologies such as data storage, data processing and analysis, forecasting and end-user services in the agriculture domain.

Cloud computing

The IoT agriculture paradigm necessitates the storage and analysis of a massive number of sensors-collected data with cloud-based services such as basic infrastructure, platform, cloud storage, data mining, ML and visualization tools[57]. Cloud-based software architecture has been suggested as a more accurate way to process and retrieve information, and perform agricultural operations[58]. The cloud adopts a centralized design featuring high latency and computational power. It is structured with an application layer at the top and a network of smart things below. Agri-Info[59] is a cloud-based system that leverages IoT technology to collect and analyse diverse agricultural data from various IoT devices in different locations. It provides agricultural information as a service to its users. CLAY-MIST[60] is an efficient cloud-based approach for tracking particular crops in real-time to provide exact and efficient decision support to farmers.

Fog-edge computing

The fog and edge layers gather data from IoT devices connected to the IoT application and help minimize latency and cost[61,62]. It can process a portion of it at the edge of the network with any device with storage, computing and network access. It is an ideal platform to enable low-energy WSNs due to its features, including closeness, location awareness, geographical spread and hierarchical organizations[63]. The features and specifications of smart farming are taken into account when deploying this technology[64].

ML/DL modelling

There are numerous types of algorithms accessible in ML, including linear regression, naive Bayes, decision tree, SVM algorithm, logistic regression, K-means, random forest, dimensionality reduction and gradient boosting techniques. To build an artificial neural network (ANN) that can learn and make intelligent predictions on its own, DL structures algorithms into layers. Basically, a convolution neural network (CNN) is used for image processing, and a recurrent neural network (RNN) is used to find traffic trends on a map. Different types of algorithms, such as CNN, LSTMS, RNNS, GANS, RBFNS, MLPs, SOMs, DBNs and autoencoders are available in DL.

In the integration of DL networks and IoT, Khalil *et al.*[65] studied CNN, such as AlexNet, ResNet, GoogleNet and VGG16. Based on the integration of data gathered by various sensors with AI systems, Vincent *et al.*[66] proposed a neural network and multilayer perceptron (MLP) based expert system which helps farmers to assess a land's potential for agriculture. With smart water management and adjusting the environment for crop growth, Bu and Wang[67] introduced a smart farming system based on deep reinforcement learning.

In order to address the problem of decentralized ML, new ML techniques such as federated learning[68] are applied, and data management systems are anticipated to be examined for farm data preservation in agricultural AI applications[6].

Big data analytics

Big data technology is a software tool that analyses, processes and extracts data from extremely complicated and large datasets that would be impossible to process using traditional methods[69]. Muangprathub *et al.*[70] introduced a system for monitoring the environment that receives information from IoT and manipulates crop parameters using relevant information about the effects of the environment through data analysis using data mining[71] on crop fields. Based on the needs of IoT applications, data analytics (DA) has been divided into various categories[72], which comprise massive analytics, real-time analytics, offline analytics, memory-level analytics and analytics at the level of business intelligence[73]. Classification, clustering, prediction and association rule are four categories that group together many DA techniques[74]. For example, ADSS mobile agricultural expert systems utilize predictive analytics to provide farmers with intelligent and precise agricultural recommendations based on big data[75].

Software defined networking (SDN)

SDN is a network architecture that achieves the separation of network control functionality, thereby creating a decoupled control plane and data plane for more flexible and programmable network management[76]. Network function virtualization (NFV) aims to separate network transfer and network services from the underlying physical hardware they run on. The data plane consists of network devices, such as switches and routers, that lack autonomous decision-making capabilities for packet routing. The southbound interface, such as OpenFlow, is utilized to implement the packet-forwarding logic defined by the SDN controller in the forwarding devices[77]. According to the policies specified, SDN controller will produce network configurations. The controller and application layer are separated by the northbound interface, which is used for a variety of agricultural service applications[18].

Blockchain technology

Blockchain technology keeps the encrypted messages in blocks to establish a chain of records in a distributed manner on each participating node and guarantees transaction integrity, ensuring that no records are falsified or erased from the ledger. Utilizing a consensus mechanism, the distributed nodes must concur on the legitimacy of transactions[27]. Here, we considered three types of blockchain: (i) Public/permission-less/open-access blockchain, (ii) hybrid/consortium/shared-permissioned blockchain and (iii) private/permissioned/closed-access blockchain[28]. AgriLedger, Ripe, AgriDigital and Agrichain are a few examples of blockchain-based smart contract systems available in agriculture[6].

Security mechanisms

Precision farming applications work on a fully data-driven approach, posing crucial security issues like authentication, availability, confidentiality and integrity attacks through data modification and rogue data injection. Ferrag *et al.*[27] performed a survey of security and privacy solutions for IoT applications, along with a discussion of how these solutions might be applied to agriculture and an analysis of blockchain-based privacy protection for agricultural applications. Granjal *et al.*[40] presented IPv6 over 6LoWPAN, as well as the routing layer, transport layer and application layer. Embedded hardware-based IoT authentication capabilities can be supported by trusted platform modules to ensure physical protection and monitoring mechanisms in IoT. The adoption of encryption algorithms, IDS mechanism, secure trust mechanism, ML-based attack mitigation and lightweight key management must take into account the limitations of IoT end devices in terms of computational power, storage capacity and battery life[18].

Application perspectives of Agriculture 4.0

IoT sensors can collect valuable information on various factors such as humidity, temperature, weather and moisture levels. This information can then be used to develop crucial real-time processes, including autonomous irrigation, monitoring of water quality, soil constituents, yield estimation and detection of diseases and pests in crops[78].

Monitoring

In agriculture, several factors need to be monitored continuously in a spatial and temporal manner to identify environmental changes, phenotyping of plants, external activity and soil and air parameters, which are considered the keystone of precision[21]. Moreover, any agriculture monitoring involves the following components:

Field monitoring: This can be done at any time and in multiple ways to detect changes in field statistics using RS methods, UVA/drone-based monitoring, autonomous robots, sensor deployment, etc. to supply real data to the end-users via an application interface. Popescu *et al.*[79] introduce an IoT device, a wireless sensor network and an UAV cooperative hierarchical system framework for agricultural field monitoring applications. Gondchawar *et al.*[80] proposed a solution for monitoring and control of field data and field activities remotely through the deployment of a GPS-controlled robot system.

Soil monitoring: This collects data on nutrients and compounds like nitrite, potash and carbon materials in the soil, as well as soil temperature, pH, electric conductivity and soil moisture. Soil monitoring tests can help increase crop productivity by recommending appropriate fertilization solutions for specific crops[81]. Angelopoulos *et al.*[82] developed an intelligent decentralized irrigation system using soil moisture sensors and mote-driven electro-valves for strawberry greenhouses in Greece.

Crop monitoring: This is a routine, close examination of plant life using RGB or multispectral cameras and IoT sensors to identify any damages done to diseases or insects. AR-IoT[83] is an application that uses a colour scale to represent crop parameters while monitoring with the support of IoT data visualization and augmented reality (AR). A low-power leaf-sensing device was suggested by Daskalakis *et al.*[84] for measuring plant water stress and temperature. To improve productivity in agriculture, it is essential to monitor crops and predict the estimated time of harvest. de Souza *et al.*[85] proposed an integrated framework that uses a combination of hardware, software, middleware and other devices to monitor crops.

Pest and crop disease monitoring: IoT-based crop disease monitoring system has been introduced to detect weeds, pests and diseases that affect wheat[86]. Image-processing technique-based monitoring is also widely used for the early detection of plant diseases[87]. Abbas *et al.*[88] categorized sugar beet plants with an accuracy of more than 85% using hyperspectral signatures. It was based on the development of spectral disease indices (SDIs) and spectral vegetation indices (SVIs) for sugar beet plants. PestNet is DL method for finding and classifying common and multi-class pests[89]. Early detection of crop diseases in agriculture can be challenging. Jiang *et al.*[90] proposed a real-time identification method for apple leaf diseases using task-specific image acquisition equipment and a set of pest image data. This method is based on a deep learning technique and enhanced CNNs.

Fertilizers and pesticides control

In the agricultural field, the most common fertilizers consist of nitrogen, phosphorus and potassium, which are primary plant nutrients. To measure the amount of N, P and K nutrients in soil, Ramane *et al.*[91] designed a Fiber-Optic sensor that utilizes the colorimetric principle, where the absorption of light by a solution in a modification of the sensor output. In addition to creating an IoT and AI-based smart fertilization system, Lavanya *et al.*[92] developed a fuzzy rule-based system that analyses soil data to determine the levels of N, P and K. They integrated the colorimetric mechanism into the NPK sensor using a light-dependent resistor (LDR) and light-emitting diodes (LED). In Faiçal *et al.*[93] study, an algorithm was designed and tested to automatically adjust the path of UAVs based on variations in wind speed and crop-spray direction.

Irrigation control

Water distribution on farms can be improved using smart agriculture. If the entire field is not evenly watered by an effective irrigation system, the quality of the crop that is produced will suffer[94]. Goap *et al.*[95] described an intelligent irrigation management system that senses soil and meteorological characteristics using ML and open-source technology. Using HTTP and MQTT protocols, Nawandar and Satpute[96] developed a cost-effective intelligent irrigation scheduling system for efficient watering based on NN and uses HTTP and MQTT protocols. A low-cost, cloud-based, autonomous watering system built on SIGFOX communication was developed by Fernandez-Ahumada *et al.*[97]. The smart water management platform (SWAMP) is an intelligent IoT-based irrigation management system that offers tools for managing irrigation in accordance with crops and soil moisture. It provides tailored data-gathering, processing and synchronization services for a variety of plants, climates and nations[98].

Weed detection

Weed detection operations must be performed using ML and DL-based algorithms to accurately detect weeds among crop plants using robotic tools or UAV image-capturing mechanisms. Bah *et al.*[99] performed image collection using UAVs and applied a DL algorithm over the collected dataset for weed detection. The DL algorithm was utilized by Kounalakis *et al.*[100] to detect weeds using the transfer learning method. For real-time weed management, Partel *et al.*[101] developed a smart sprayer that uses CNN and NVIDIA GPUs. To classify weeds, Lottes *et al.*[102] introduced the method of semantic segmentation of images based on pixels, dividing them into soils, crops and weeds. Based on a condensed training set, Potena *et al.*[103] designed a setup of the multi-spectral camera placed on the ground-based agricultural robot for real-time precise weed classification.

Harvesting and yielding

To achieve precise harvesting time, optimize yields, reduce environmental effects and save costs, precision agriculture uses variety of technologies, including sensor nodes, GPS, ML/DL algorithms and big data[104]. The smart harvesting system mainly consists of essential features like obstacle detection, robotic arms, motion control, fruit classification, colour and shape identification, object detection and optimal harvest date[18]. Megalingam *et al.*[105] developed a robotic arm for trimming and gathering fruits from trees, which connected via Bluetooth to control arm motion using a mobile application. According to three different criteria, including colour, depth and shape, an algorithm for guiding harvesting robots to autonomously pick up apples has been presented by Lin *et al.*[106]. Xu *et al.*[107] suggested a technique to determine the best time to harvest corn in the field using multi-spectral RS data.

Challenges and issues

This section highlights the challenges and issues that remain unresolved and may be contributing to the slow adoption of IoT in the agriculture industry.

Lack of standards

The new challenge of IoT agriculture is crucial to establish data exchange and communication standards that can connect various systems to form a unified and comprehensive agricultural exploitation system. It is important to have validated standards for data and process representation to ensure that any technological choices remain interoperable with newer equipment and receive enduring support from the manufacturers and other industries during the lifespan of an agricultural equipment. With standardization, interoperability issues can be resolved, enabling a unified system to cover all aspects of agricultural exploitation[2].

Hardware challenges

Basically, in the agriculture sector, the deployment of IoT components in the air, on the field and underground helps cover remote areas. Therefore, appropriate programming tools and low power potential are required, as instant battery replacement is challenging during a power outage, especially in a vast open field[108]. In order to assure efficiency, developing IoT systems for open-field deployment needs more sensors to monitor the environment and the crops as they grow.

Security challenges

IoT devices are susceptible to physical interference, including theft, animal and predator attacks, link changes and physical address modifications[109]. Attempts like device capture attacks could target the IoT-enabled, location-based service that is utilized for precision farming[110]. A network can be compromised by congestion attacks, virus injects, forwarding attacks and denial of service. Data security and confidentiality must be considered in the middleware layer. By authorizing specific entities, one can ensure that only authorized users can access application-layer data[14]. For IoT devices, due to limited resource constraints like limited memory, poor connectivity, computational capabilities and power consumption, it is not feasible to implement complex and sophisticated algorithms. So, hardware constraints should be taken into account while developing encryption methods, key distribution, intrusion detection techniques and routing policies[111].

Technical issues

IoT-based agriculture solutions face various technical issues at different stages of the framework, such as reliability, interoperability, scalability, interference, localization, resource optimization and quality of services in real-field deployment.

Interoperability: A wide variety of IoT equipment manufacturers is available, which creates a heterogeneous environment due to a lack of common standards and protocols. So technical, semantic, syntactic and organizational interoperability will arise in actual deployment. Technical interoperability is about different protocols and infrastructures that enable IoT devices to communicate[112]. To ensure interoperability in data exchange, various data-transfer formats such as Extensible markup language (XML) and JavaScript object notation (JSON) have been adopted. Semantic interoperability refers to the understanding of information shared between individuals.

Scalability: Deployment of IoT-based agriculture is not limited to a specific region; it can be scalable with other existing infrastructure. The network applications and back-end databases for IoT in agriculture must be dependable and capable of handling increasing demands, as the addition of various end-user applications makes the operations more complicated over time. To ensure this, it is crucial to design a highly scalable security plan and an intelligent IoT system for each end device[3].

Latency and dependency: Mainly, cloud-based applications require ubiquitous high-bandwidth internet connectivity. So, we must ensure that no outage and resource constraints in cloud connectivity arise in IoT systems. Also, it has a high dependency and high latency in the case of remote areas of agriculture. These issues can be resolved by placing a fog and edge layer near IoT devices to analyse data in real time near the edge of the network.

Optimization: To deploy IoT equipment in the agriculture field, it must be ensured that the number of IoT sensors, sink nodes, gateway, cloud service and communication topology optimize resources. However, due to different farm sizes, variability in crops and other constraints of deployment, one model of resource optimization is not suitable for all cases and causes other challenges like performance degradation, bandwidth and latency issues, etc. Determining the resource distribution for the highest possible agricultural yield would, therefore, require sophisticated mathematical models and algorithms.

Interference: Particularly for IoT devices employing unlicensed spectrum like LoRa, WiFi, ZigBee and Sigfox, it provides barriers to lowering dependability and data loss. The licensed spectrum of a cellular network is useful for ensuring reliable communication, but due to band restrictions, using non-orthogonal multiple access techniques might present challenges[21].

Localization: Before deploying IoT devices in agriculture, factors such as the ability of the device to enable localization, minimal configuration and location, sufficient information gathering and dependability without generating interference must be taken into account[113]. Additionally, the capability of supporting static IoT device deployment in areas without prior knowledge of the mobile IoT infrastructure, as well as IoT device roaming for mobile IoT devices, must be considered.

Use case of Agriculture 4.0

The main objectives are to enhance agricultural productivity in resource-constrained environments by adopting agriculture 4.0-oriented advanced solutions such as drones, autonomous robots, smart tractors, web applications and farm management solutions. The agricultural use cases for future farming are presented below.

Agriculture drones and UAVs

In order to monitor the field for soil analysis, crop health classification, planting, crop spraying, plant counting and height measurements, drainage mapping and weed pressure, the drones are equipped with GPS devices, cameras and sensors[3]. Due to their great speed and efficiency during spraying, these drones effectively spray pesticides and fertilizers[86]. Drones equipped with sensors are being used to survey, imaging and map agricultural lands. Additionally, these sensors enable the collection of farm data with respect to a variety of characteristics, including air pressure and wind speed. The weight and size of spectral cameras have significantly reduced due to developments in spectral imaging technology, making it easy to place them on drones or quad-copters. Spectral cameras installed on drones can take images with stacks of high-resolution at a variety of wavelengths and up to 10 bands[24].

Intelligent farm robots

Harvesting the crops in a timely manner is essential, as either early or late harvesting will significantly reduce the yield. So, to automate and design a more specialized harvesting mechanism, the use of robots like fruit harvesting arms has increased. Mao *et al.*[114] designed a stereo vision for apple orchards that uses distance finding between the robot and the fruits to be harvested to distinguish them. Thangavel and Murthi[115] proposed a system that uses key image extraction and optical flow techniques to harvest tea leaves. The system utilizes a robotic arm that selectively plucks the tea leaves

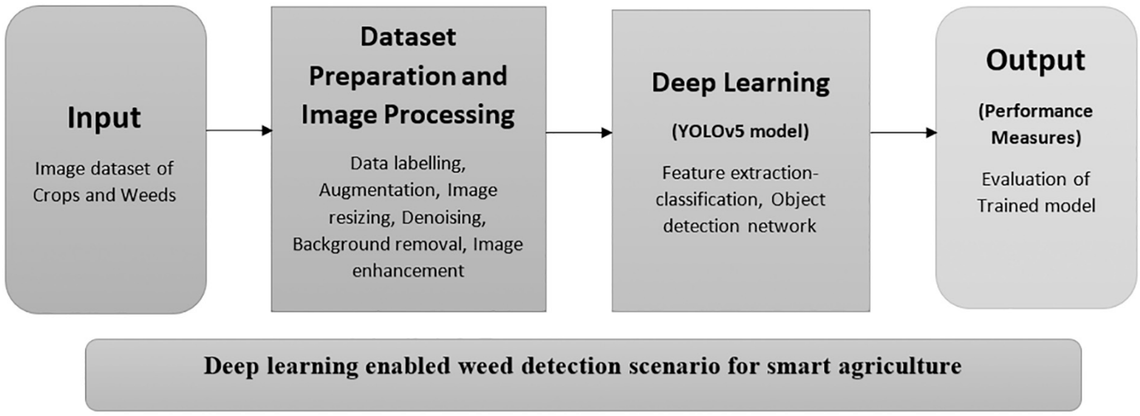

Figure 2. Deep learning-enabled weed detection scenario.

based on their quality. The Robocrop In-row Weeder uses a weeding mechanism, control system and machine vision to mechanically eliminate weeds between crop rows[116]. It uses RGB colour cameras to identify crop plants and then utilizes internal computation to identify the crop's centre, which the mechanism will rotate around[24].

Autonomous and smart connected tractors

To meet the expectations of Agriculture 4.0, agricultural equipment producers must develop autonomously powered and smart-linked tractors, in addition to cloud-computing infrastructure[8]. With powerful computational software and equipment, a low-cost tractor monitoring system has been designed that keeps track of the health of the tractor and notifies users when any problems arise. These self-driven tractors have the advantage of avoiding previously cultivated rows or areas that are separated by less than an inch to increase precision and reduce errors during the spraying of insecticides. To safeguard the security of both agriculture and people, a smart tractor will devise operating paths and intelligently avoid obstacles in the field[117]. These tractors are automatically guided by GPS devices to plough the fields in perfectly straight rows with variations of no more than 2 inch. This enables farmers to cover more areas with higher accuracy in less time and use less fuel, chemicals and fertilizers by planting seeds, applying fertilizers and herbicides with a similar level of precision.

Smart agriculture applications and web services

The application layer is involved in delivering accurate information, notifications, predictive results and alerts to the farmers, mainly on their smartphones. In order to provide users with specific responses to their questions using the web resources, Niranjan *et al.*[118] presented a chatbot based on the DL-based RNN framework. In addition to maintaining regular checks over greenhouses and fields, E-Kakashi is another cloud platform connected by NB-IoT cellular network that also manages the environment inside a greenhouse, including temperature, humidity and carbon dioxide emission[24].

Case study on weed detection for smart agriculture

Here, we focused on a real-time weed detection system using the YOLOv5 model for an agriculture field. This model is a DL model based on the PyTorch framework to detect objects in real time with high accuracy[119]. The YOLOv5 model was trained on the D5 dataset, which has a total of 600 object categories and is based on the EfficientNet architecture. The centroids of the clusters are used as the anchor boxes in the model to determine the size and shape of objects. The dynamic anchor boxes use a clustering method to group the ground truth bounding boxes into clusters. Additionally, it uses the spatial pyramid pooling layer to reduce the spatial resolution of the feature maps, which helps to enhance the detection of small objects because it enables the model to view objects at different scales. The YOLOv5 model is trained by the system using an image dataset of crops and weeds. The algorithm is trained to recognize weeds in the images and differentiate them from crops. The configuration for training is broken down into three YAML files: the hyperparameters configuration file specifies the hyperparameters for the training, the model configurations file specifies the model architecture and the data-configuration file explains the dataset parameters. Finally, depending on the task for which the model was trained, different metrics can be used to assess the output of a DL model, including classification matrix (accuracy, precision, recall, F1 score) and regression metrics (mean absolute error, mean squared error, root mean squared error). Figure 2 is a detailed representation of the workflow for weed detection scenarios for smart architecture.

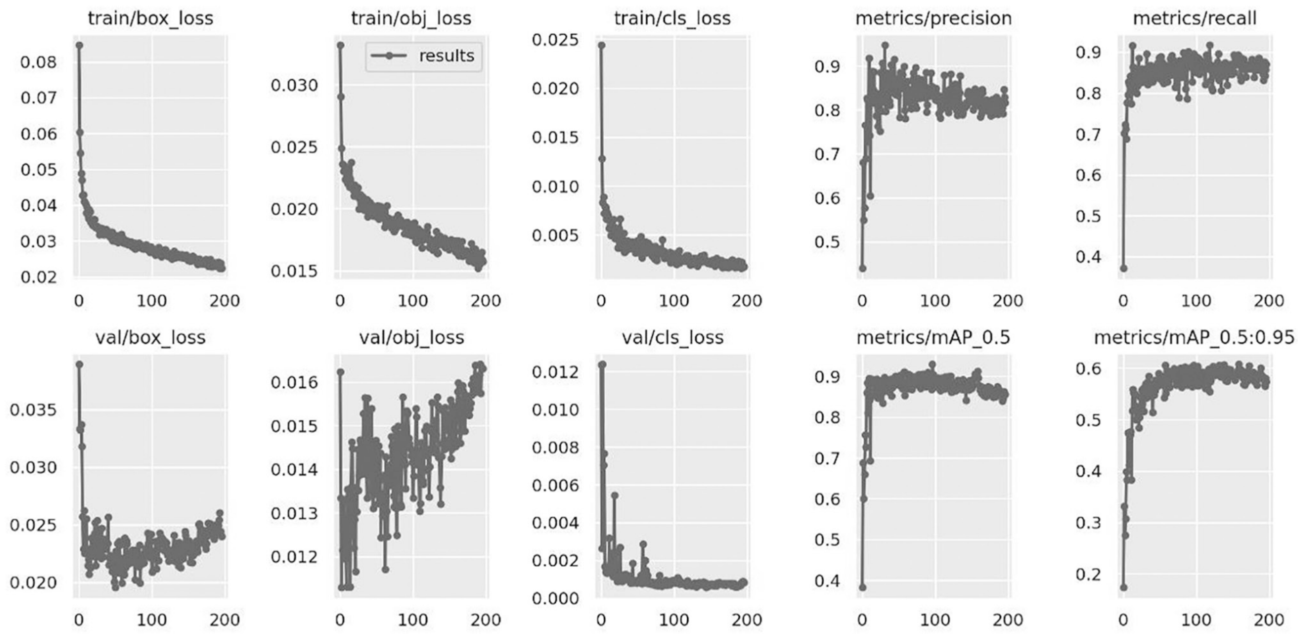

Figure 3. Results of feature extraction training and validation.

We trained and tested our model using a Kaggle dataset on crop and weed identification data with bounding boxes for this implementation scenario. The collection included 1300 images of different types of weeds and sesame crops, each with a bounding box annotation and an image label. Each image was 512×512 in colour, with YOLO-formatted labels for each of them. There were two data classes in this dataset: crops and weeds. The dataset was subsequently divided into training and validation sets. We employed Google Colab, a cloud-based development environment, for implementation. The YOLOv5 repository was then installed by cloning it from GitHub as the next step. The YOLOv5 train.py script was used to train the model after the dataset was constructed and configured. After the training was completed, the model was run on the validation dataset to assess its performance. As a hyperparameter that controls how the ML model is trained, we have considered 640 images for the training dataset with a batch size of 8 and 250 epochs. The best model is saved as the best.pt file, and the best results were seen at epoch 96. It halted training early after 197 epochs were finished in 1.291 h because there was no improvement in the final 100 epochs. The performance of the proposed scenario was assessed using a variety of measures on the training set. It achieved a precision of 85.20%, recall of 89.60% and mAP of 93%. Figure 3 presents some common metrics for evaluating the output of DL models. YOLOv5 losses and metrics must be determined using three components: box loss, obj loss and cls loss (cross-entropy). Precision, recall and mean average precision at the intersection over a union threshold of 0.5 are three metrics used to determine the accuracy of bounding box predictions. As shown in Figure 4, we can use a confusion matrix to visualize the model's classification performance of the model and identify the different types of errors. Once the model is trained and evaluated, we can use it to detect weeds in new images. This algorithm can be used to automate the process of weed detection in crops in conjunction with smart agriculture technologies like drones and robots with cameras. Thus, farmers can increase crop yields and reduce the usage of herbicides by promptly spotting and eliminating weeds, creating a more sustainable and effective agricultural system. Using the YOLOv5 model, the system can also be expanded to detect pests and diseases in the field.

Conclusion

The expansion of IoT has changed traditional agricultural practices into smart precision-based standard Agriculture 4.0. This article analyses the current state and advancements in the field of smart agriculture, resulting from the expansion of the IoT paradigm. Initially, it covers the significant issues in the agriculture domain and emerging potential solutions, as well as layer-wise architectural building blocks and technical support deliverables for diverse agriculture scenarios. Next, it presents an overview of the current state of IoT-based agriculture and other integrated technology-related literature, as well as emerging trends in integration with IoT-based Agriculture 4.0. It examines real-world use-cases and smart agricultural scenarios of IoT in agriculture, along with how these technologies can affect upcoming developments in smart agriculture. We have thoroughly explored how these technologies can affect upcoming

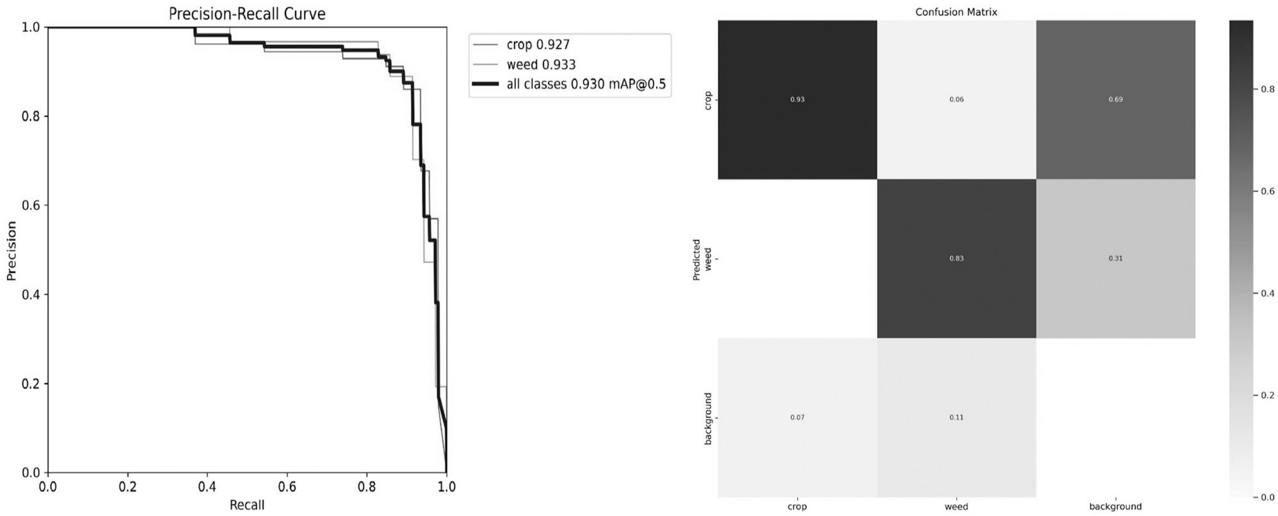

Figure 4. Results of precision-recall curve and confusion matrix.

developments in smart agriculture, including UAVs, unified web solutions and other smart farming equipment. Finally, the challenges associated with the adoption and implementation of IoT-driven agriculture are discussed.

Conflict of interest: The authors declare that they have no conflict of interest.

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