This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.XXXX.DOI

AgriFusion: An Architecture For IoT And Emerging Technologies Based On A Precision Agriculture Survey

RITESH KUMAR SINGH, (Student Member, IEEE), RAFAEL BERKVENS, (Member, IEEE), and MAARTEN WEYN, (Member, IEEE)
IDLab, Faculty of Applied Engineering, imec, University of Antwerp, 2000 Antwerp, Belgium

Corresponding author: Ritesh Kumar Singh (e-mail: riteshkumar.singh@uantwerpen.be).

This research is funded by the European Union Interreg V Flanders-The Netherlands program's project 'Grow!' on greenhouse monitoring, co-funded by the Flanders Innovation and Entrepeneurship Agency, the Dutch ministry of Economic Affairs, the provinces of North-Brabant, Antwerp, and Flemish-Brabant

ABSTRACT Precision Agriculture (PA) is a management strategy that utilizes communication and information technology for farm management. It is a key to improve productivity by using the best agricultural practices and optimal usage of resources. Agriculture faces diverse challenges due to soil degradation, climate variation, and increasing costs. To unfold these challenges, PA uses Wireless Sensor Networks(WSNs) and exploits acquisition, communication, and processing of the data as basic enabling technologies to amplify the crop yield. Also, many other multidisciplinary technologies are supporting PA in finding the most novel use cases for PA. The use of Machine Learning (ML) and Artificial Intelligence (AI) has transformed PA at almost every level. The fog/edge paradigm is mitigating many challenges such as network bandwidth and security by bringing computation closer to the deployed network. At the same time, Software Defined Networks (SDN) brings flexibility, big data assists in handling data, and nano-technology plays a crucial part in driving the innovation in PA. This paper delves into ways these technologies are transforming PA in respective tracks, exhibiting the significance of integrating multidisciplinary approaches towards the future of PA. In addition to a comprehensive survey, this paper proposes a multidisciplinary architecture: AgriFusion, for efficient and cost-effective agriculture solutions. A list of industrial solutions for different aspects of farm management and their underlying focused technology have been highlighted. This can help to align research and industrial goals for PA. Furthermore, this paper defines a step approach to describe the performance dichotomy between resource availability and objectives for PA. In addition, solution architecture is proposed for designing Key Performance Indicators (KPI) in PA. In the end, some open research issues in implementing PA and respective future scopes have been presented.

INDEX TERMS Internet of Things (IoT), Key Performance Indicators (KPI), precision agriculture, smart farming, sensor networks

I. INTRODUCTION

THE Internet of Things (IoT) in recent years is directing a paradigm shift in all the areas of human-machine interaction. From the healthcare industry to manufacture and from agriculture management to infrastructure, IoT has been massively adopted. The projections from IoT Total Addressable Market (TAM) show that the number of IoT-connected devices in the world will grow from 7.6 billion to 24.1 billion, with revenue tripling from USD 465 billion to over USD 1.5 trillion [1]. There is a rapid shift evolution from conventional agriculture to farm management being controlled by different IoT companies. The adoption of advanced IoT technologies is helping growers in producing higher yields from farms for catering to the rising demand. According to the new market research published by Meticulous, the agriculture IoT market is expected to grow at a Compound Annual Growth Rate (CAGR) of 15.2% from 2020 to reach $32.7 billion by 2027 [2]. The technology advancement in IoT is allowing both small and large-scale farmers to implement Precision Agriculture (PA), which is a data-based manage-

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

ment approach for farms to enable optimization, responding to variability in crops.

The key features of IoT include battery-constrained sensor nodes connected over a network, supporting data sensing, and post-collection analysis. An explanation for the phrase "IoT" as put forth by IEEE, is *"a network that connects uniquely identifiable Things to the Internet. The Things have sensing/actuation and potential programmability capabilities"* [3]. IoT essentially uses connected devices to perform a plethora of tasks like process monitoring, environmental sensing, and health monitoring. Wireless Sensor Network (WSN) are the most crucial underlying technology for IoT. A WSN is a network formed by deploying sensors to collect and forward the data to the enterprise/cloud for further processing. This precise data from the sensors, aerial devices, and IoT solutions are used for predicting climate change, increasing farm productivity with environmental sustainability, monitoring, and having a proactive reaction to crop performance. It also helps in choosing a suitable crop by observing and measuring the demand or dependent factors.

Consumer demand for agriculture is growing rapidly (59% to 98% by 2050) [4] with an increased proliferation of technologies. The demand builds inevitable pressure on farmers, resulting in different sources of stress such as plunging commodity prices, increasing debt, and usage of chemicals. In the last few years, several thousands of farmers have committed suicide because of crop insecurity, which deserves decent attention [5]. Farmers are also faced with dwindling fossil fuels, limited natural resources, and changing climate. To tackle this foremost issue, farming has seen a major transformation towards a more industrialized and technologically driven approach. Characteristic features of generic PA and IoT-based PA is mentioned in Section II and shown there in Table 2. IoT technology carries a high potential in the sphere of agriculture to transform agriculture in several aspects, primarily by lowering the production risks. It provisions a farm management concept that uses a combination of data, sensors, and communication to tailor the farming requirement. By using various smart devices, farmers can predict better with an improved efficiency that promotes sustainable growth while cutting resources. Data collected from the sensors are used to track the state of the crop growth and foresee the output of the production. It also helps to see any anomalies along with timely mitigation of the risks on crop growth. Few smart automated IoT solutions such as fertilizing, irrigation, or pest control can enhance crop quality and achieve high volumes.

Precision agriculture is continuously evolving according to the advances in the underlying IoT technologies. This evolution aims at achieving a set of key features to improve efficiency and boost crop yields. These features include (a) Data metrics for monitoring (b) Decision making (c) Crop protection and management (d) Reduce waste and operational cost (e) Crop variability (f) Data trend for several use-cases and (g) and Pests control. Core features responsible for designing and comparing Key Performance Indicators (KPI)s

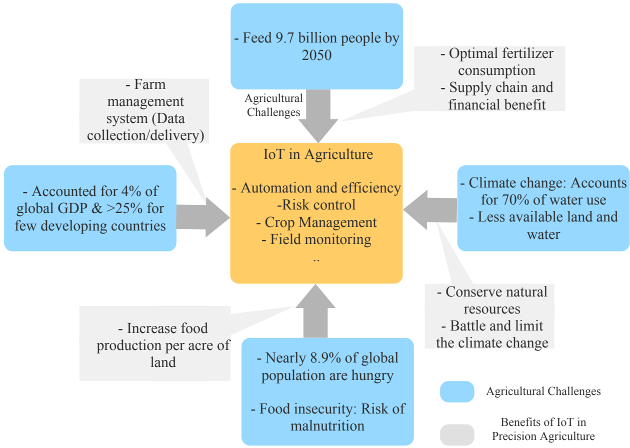

FIGURE 1. A schematic representation of IoT enabling the demand for precision agriculture and smart farming. [7]

of precision agriculture depend upon technological factors such as sensors, mobility, real-time monitoring, connectivity, and ease of application deployment. The next industrial revolution is having the agricultural sector already on board and farmers are adapting the innovative technologies to meet the food demand [6]. This empowers farmers to get the support of farming decisions at the right time, right place, and importantly with the right inputs.

The instigation of new technologies provides more tools for fine-tuning and boosting PA decision-making. Wider digitization of agri-food (producing food agriculturally) production is enabling optimization and precise utilization of inputs, that results in positive environmental impact. The overall performance of PA is increasing with the utilization of new technologies. Introduction of Machine Learning (ML) optimizes the entire application by augmenting error correction, security, predicting traffic, data processing, and resource management. One of the most important requirements for the PA is low latency, it can be achieved by providing computation power locally in the network through edge or fog computing. The Sensor Node (node) are conventionally energy and computation restricted, but light-weight processing at the edge helps in interoperability and isolating the node from the core network. The sensors deployed for PA generate a large volume of data. Thus, big data is an important aspect in enabling real-time analysis and context awareness. Blockchains also enhances precision agriculture by making the solution efficient, fast, and secure. Other emerging technologies like Software Defined Network (SDN) and Artificial Intelligence (AI) help in the virtualization of the network in real-time. This leads to improved resource and energy utilization and enhanced responsiveness for the application.

Motivation: Current statistics point to the requirement of food with the declining availability of natural resources, along with the explosive proliferation of IoT devices. The food and agriculture organization of the United Nation reports that: *"The world is not on track to achieve Zero Hunger*

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

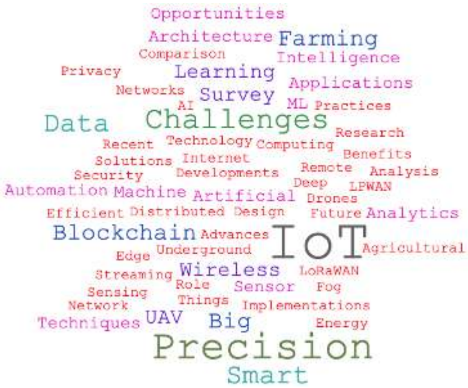

FIGURE 2. Research trend analysis using survey word similarities to demonstrate the usage of multidisciplinary technologies for precision agriculture.

by 2030. If recent trends continue, the number of people affected by hunger would surpass 840 million by 2030" [8]. Figure I shows the agricultural challenges that need immediate attention through PA and IoT. It also illustrates the major application domain that can be covered with an IoT solution to handle the agricultural challenges. Agriculture is projected to be one of the crucial and dominant applications of IoT. The requirements for IoT solution to achieve PA differs from crop to application-specific use-case. AI, ML, nanotechnology, energy-efficient framework, and development of the sensor networks are transforming the entire PA solution. Energy harvesting and remote sensing have revolutionized the network management, design, and architecture of the PA framework. Blockchain and big data are helping in fast analysis and diagnosis with enhanced privacy features. There are fair amounts of comprehensive surveys that explore PA and underline standalone technology. However, this study aims at integrating all the emerging multidisciplinary technologies and presenting a comprehensive review of their use in PA. This becomes much relevant as, one of the reports by BBC says: Algorithms, drones, and robots can make farming a lot friendlier to the environment but need to work in collaboration [9].

Contribution: This paper targets to present an in-depth survey of different technologies contributing to PA. Agriculture is transforming with the advances in different technologies as shown in Figure 2, there is a necessity to accumulate and unify the work. We can outline our contributions as depicted in Figure 3 and described below,

1) We provide an overview on relevance and requirement of the PA in current state-of-the-art.
2) Various PA solutions and architectures based on different applications are presented.
3) We explore, classify, and analyze the complementing future technologies for PA. The literature on ML, AI, edge computing, blockchain, nano-technology, remote sensing, energy harvesting, WSN, cloud and edge/fog based computing, different IoT architectures, and simulators in the context of PA is presented. To the best of our knowledge, this is the first work that does a comprehensive survey on interdisciplinary emerging technologies in the context of PA.
4) Our main contribution lies in introducing the significance of the fusion of multidisciplinary approaches for the future of PA. We propose these technologies at each layer of IoT for an optimized architecture as AgriFusion.
5) The analysis of industrial solutions for PA and their focus technology is briefly discussed, identifying the trend and map the industrial development with research scope.
6) We list and propose a generic step approach to designing the KPIs for any PA application.
7) Finally, we identify the future research directions in PA that exploits the novel technologies along with open issues based on a literature survey.

We have aimed to layout a consolidated state-of-the-art survey for the research community that would be instrumental in the adaptation and deployment of optimized PA. Table 1 gives an overview of the technology coverage of available survey papers in contrast to our work. Most of the survey papers are technology specific, however in contrast this work covers all the technologies aligned with PA.

Paper Organization: The paper organization is as follows. Section II covers the related work and Section III gives a brief description and alignment of IoT with PA. Section IV describes the basics of emerging technologies for PA. Section V discusses the industrial-based solutions and framework used for PA along with their focused technology. Section VI discusses the implication of KPIs and its designing process for the PA. Section VII unfolds the multidisciplinary architecture for PA. Section VIII identifies future research directions along with open challenges in implementing PA, and the last Section IX presents the conclusion. Structure of the paper and our contribution can be visualized through Figure 3.

II. RELATED SURVEY PAPERS

Precision agriculture is the term coined after variously described smart farming notions like site-specific, prescription farming, and variable rate technology for crop management. IEEE has several standard frameworks, among which P2413-2019 and IEEE 1451-99 [39] feature architectural framework of the IoT and security harmonization respectively. These standards are used for the implementation of IoT for PA applications, where sensors and other devices can interoperate and collaborate without caring about the underline communication. Each day, there's plenty of development in IoT applications, specifically in PA. Figure 4 shows the three-tier architecture of an IoT solution for attaining precision agriculture within the greenhouse. It shows different components and interactions of data acquisition, data analysis, and end-user application. Data acquisition is done in the greenhouse by deploying the sensors. Data collected by these sensors is forwarded to the gateway, followed by the cloud for data analysis and data mining. The extracted and meaningful information is shown in the application. All of these

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

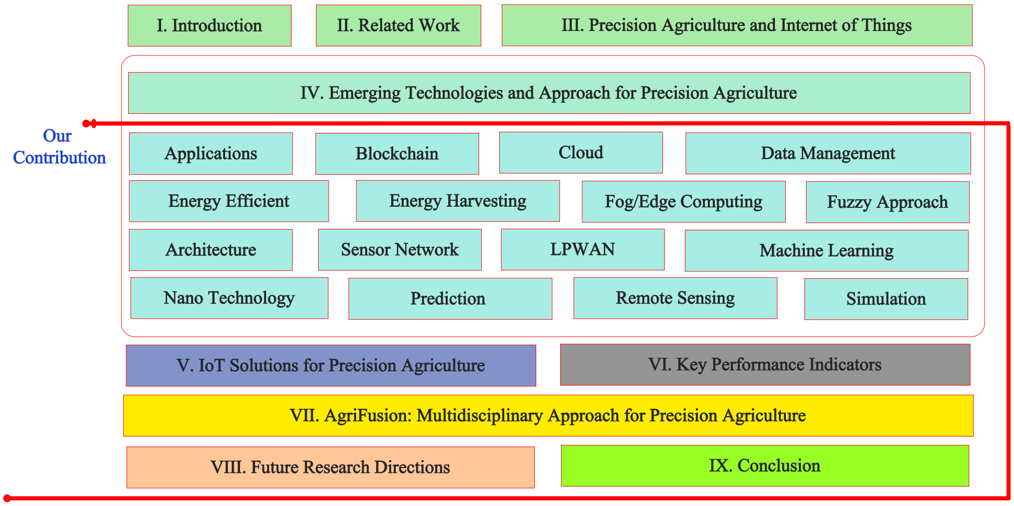

FIGURE 3. Structure of our survey.

interactions are supported by different technologies, such as WSN, ML, AI, and likewise. The current literature explores the association of various technologies for the PA thoroughly.

The various aspects of technologies and protocols involved in the domain of agriculture is briefly covered in the review [27]. It explores the major components of IoT that can be instrumental for smart farming, along with the introduction to the various network topologies and network architectures mapped with the layers of IoT. It connects IoT-based technologies like big data, cloud computing, and analytics to agriculture applications and also touches on the security issues in agriculture. This survey doesn't cover other major technologies such as ML, AI, and insights into the fog and edge computing. This gap is filled by building a distributed model based on the agent for computing paradigms in [34]. It proposes a communication architecture to automate the installation using operating rules and smart processes, but eventually lacks in including ML and AI services for further optimization. The survey by Tzounis et al. [18] is a detailed overview of recent IoT technologies and their potential value towards the agricultural sector. It delves into cloud computing, fog computing for the aspect of resource utilization, and big data to improve and automate real-time processes. It also brings the concept of interoperability among heterogeneous devices to provide the added value of WSN as potential value for future farmers. Literature review of different IoT applications in the agriculture sector is done in [29]. It covers WSN, communication protocols, and different network types of IoT along with the major underline challenges in the field of agriculture. It also discusses the country's policies for IoT-based agriculture but suffers from a deficiency in terms of its discussion which is limited to projects and approaches. It leaves out many aspects such as ML, network management, and other emerging technologies in its discussion.

The review on big data technologies in the IoT domain is done in [10]. It explores state-of-the-art across big data technologies and suggests a conceptual framework. It suggests how certain big data technology can be adapted to other IoT domain applications. The discussion could have been enriched with the inclusion of other technologies along with covering big data. The survey by Wolfert et al. [11] and Kamilaris et al. [13] expands the scope of big data applications beyond smart forming towards the food supply chain. The review aims to cover related socio-economic challenges which can be solved through big data applications. It exhibits the interesting proprietary systems where a farmer is part of a collaborative system for food production. This paper is crucial due to bringing technological aspect in socio-economic perspective, however lacks to bring in other technologies supporting the economic growth. In contrast, Wolfert et al. [11] takes an in-depth look into the advances of big data in various industries and converges the approach for agriculture application. It covers the study of around 34 solutions including tools algorithms and dimensions of big data along with the analysis of overall impact. It reflects the opportunities of big data for smart farming. In the end, it proposes the requirement for the openness of data resources for academic research and business ventures in the agricultural domain.

IoT technologies such as radio frequency identification, cloud computing, WSN, and other applications enabling smart agriculture are discussed by Elijah et al. [22]. It showcases opportunities and trends towards application scenarios and business, also emphasizes using data analytics over IoT for enhancing productivity in the agriculture sector. The critical aspect of future trends and opportunities carries the

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

TABLE 1. Comparison of the State-Of-The-Art for precision agriculture with our work.

Group →	PA Application Oriented				Technology specific Survey				Architecture / Framework		
References \ Technology	WSN / LPWAN	Remote Sensing	Cloud	UAV	ML / AI	Blockchain	Big data	DL / NN	Fog / Edge	Architecture	Data Management
Mouzhi Ge et al. [10]	x	x	x	x	x	x	✓	x	x	x	x
Wolfert et al. [11]	x	x	x	x	x	x	✓	x	x	x	x
Radoglou et al. [12]	✓	✓	x	✓	x	x	x	x	x	x	✓
Kamilaris et al. [13]	x	x	x	x	x	x	✓	x	x	x	x
Khanna et al. [14]	✓	✓	x	x	x	x	x	x	x	✓	x
Torky et al. [15]	✓	x	x	x	x	✓	x	x	x	✓	x
Cisternas et al. [16]	✓	✓	x	✓	x	x	x	x	x	x	x
Glaroudis et al. [17]	✓	x	x	x	x	x	x	x	x	✓	x
Tzounis et al. [18]	✓	x	✓	x	x	x	✓	x	✓	✓	x
Vuran et al. [19]	✓	✓	✓	x	x	x	x	x	x	✓	x
Boursianis et al. [20]	✓	x	✓	✓	x	x	x	x	x	✓	x
Jha et al. [21]	✓	x	x	x	✓	x	x	✓	x	x	x
Elijah et al. [22]	✓	x	✓	x	x	x	x	x	x	✓	✓
Mohammadi et al. [23]	x	x	x	x	✓	x	✓	✓	✓	x	x
Kulbacki et al. [24]	x	✓	x	✓	x	x	x	x	x	x	x
Ali et al. [25]	x	x	x	x	x	✓	x	x	x	x	x
Ayaz et al. [26]	✓	x	✓	✓	✓	x	x	x	x	✓	x
Farooq et al. [27]	✓	x	✓	x	x	✓	✓	x	✓	✓	✓
Kour et al. [28]	✓	x	✓	x	✓	x	x	x	x	x	x
Farooq et al. [29]	✓	x	✓	x	x	x	✓	x	✓	x	x
Bodkhe et al. [30]	x	x	x	x	x	✓	x	x	x	x	x
Tsouros et al. [31]	x	✓	x	✓	x	x	x	x	x	x	✓
Mekonnen et al. [32]	✓	x	x	x	✓	x	x	✓	x	x	x
Sishodia et al. [33]	x	✓	x	✓	x	x	✓	x	x	x	x
Francisco et al. [34]	✓	x	x	x	x	x	x	x	✓	✓	x
Shafi et al. [35]	✓	✓	x	✓	x	x	x	x	x	x	✓
Thakur et al. [36]	✓	✓	x	x	x	x	x	x	x	✓	✓
Vitali et al. [37]	✓	✓	x	✓	✓	x	x	x	x	✓	x
Ferrag et al. [38]	✓	x	x	x	x	✓	x	x	✓	x	x
This Work	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

interoperability between different technologies, which is not discussed in this paper. A brief overview of various WSN technologies is presented by Thakur et al. [36]. It covers the different environmental parameters for achieving precision agriculture on different crops and also highlights different sensors and communication technology used for PA. Several research questions are designed in the discussion, but it does not include the coverage of future applied technologies. The survey by Glaroudis et al. [17] attempts to focus on the basic characteristics and performance of the IoT application for agricultural use cases. It provides KPIs to highlight the suitability and challenges for an efficient implementation of smart farming. This survey is a very brief classification of the IoT protocols but does not identify the potential in adopting future technologies based upon the underlying methods. In contrast, Cisternas et al. [16], identifies the type of technologies, framework, and their comparison to decide which implementation suits the most. The findings of this paper discuss that remote sensors are the most used technology, but in essence do not compare or discuss other emerging technologies and network management functions. The study did by Khanna et al. [14], does the comprehensive observation of IoT in regard to the upward market trend. It covers the functional aspect of the IoT domain, connectivity along with open issues but leaves an open-ended question - "What will derive next generation of PA when technology is not constant?". This question is answered through this paper, i.e. integration of technologies towards common application objective is the key for PA.

The overview of emerging technologies such as big data, remote sensing, and the use of Unmanned Aerial Vehicle (UAV) are shown in [12]. It emphasizes using remote sensing technologies for better crop production, as remote sensing is rapidly increasing in the past few years with the availability of high-resolution images. UAVs play an important role in powering remote sensing in PA applications. In the same context, the author also discusses the use of UAVs for obtaining high-resolution images for PA applications. It covers the spectrum of technologies but exhibits the challenge to integrate all and come up with a reliable workflow application.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

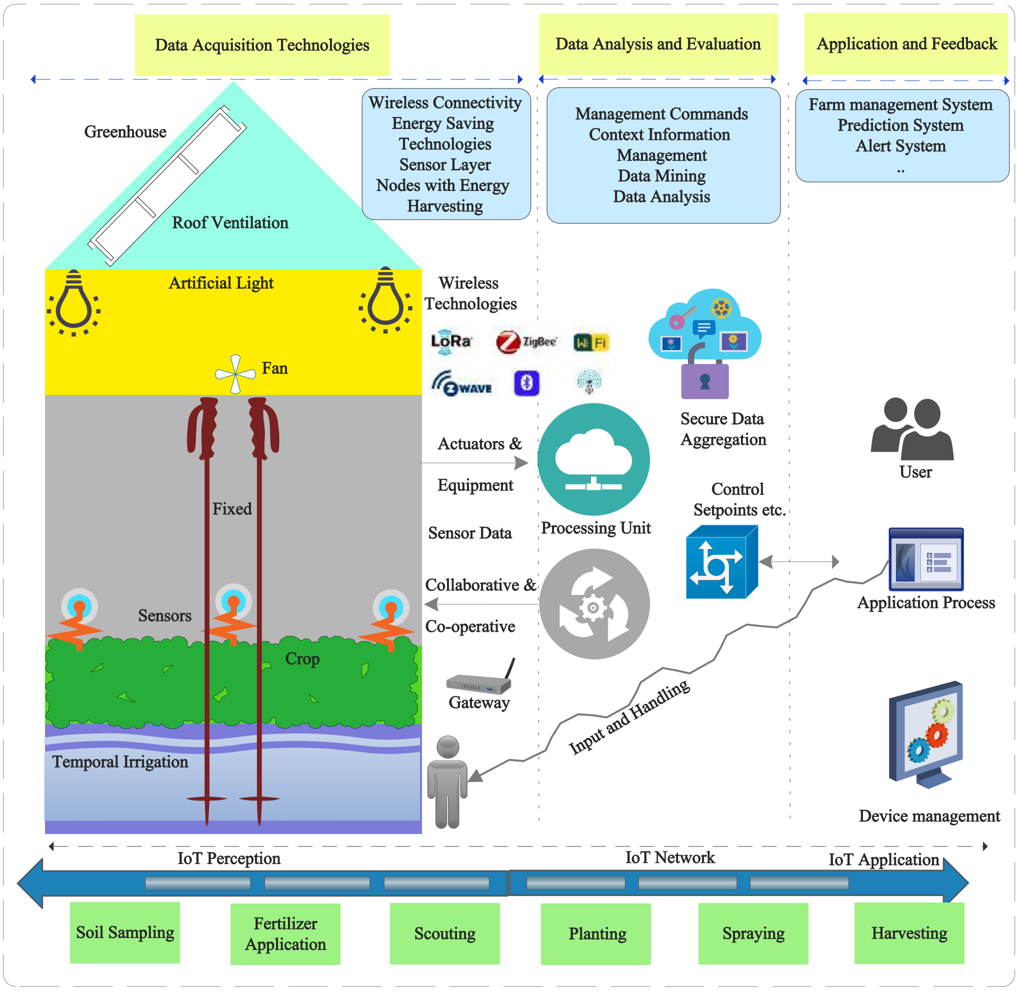

FIGURE 4. A schematic representation of the three-tier architecture of the IoT solution for precision agriculture in a greenhouse. The figure demonstrates data acquisition from the greenhouse, analysis, and application.

The survey by Boursianis et al. [20], Kulbacki et al. [24], and Sishodia et al. [33] provides an overview of the potential use of UAVs in PA. It focuses on soil mapping and production mapping using Global Positioning System (GPS) data by examining the different methodology and applications for aerial crop monitoring and other tasks such as sprinkling over the crop. Over time, UAVs have increased capabilities and have expanded their applications in complex terrain. Drones help in providing high-quality remote sensing by providing spectral imaging. It gives a nice sketch of remote sensing combined with UAVs for agriculture operations like Variable Rate Application (VRA) and displays the role of UAVs in various sectors of PA including weed management, plant growth, and crop disease management. It helps in transforming traditional practices into bringing intelligence but can be further exploited by using ML and AI along with edge computation for power efficiency and analysis.

The security and privacy-preserving technologies for adaptation of IoT technology in agriculture are covered by Ferrag et al. [38]. The main focus of this work is on blockchain based solutions, along with a consensus algorithm for PA. It also provides a classification of threat models, privacy, and integrity properties for IoT-based agriculture solutions. The detailed study of the blockchain in IoT-based PA solutions is undertaken by Bodkhe et al. [30] for an efficient trustworthy and secure ecosystem. The survey proposes an analysis of traditional solutions in regard to attacking models to maintain trust and transparency in deploying blockchain for irrigation systems. It includes the study of country-specific projects that can be referred to as blockchain based agricultural solutions. Besides, Torky et al. [15] proposes novel blockchain models specifically for the IoT-based agriculture systems. There remains a lot of research directions in the security space of blockchain that is discussed by Ali et al. [25]. It brings the attention of leveraging blockchain with emerging technologies such as big data and ML along with tackling

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

TABLE 2. Characteristic features of generic PA and IoT enabled PA with the help of progressive technologies.

Sr. No.	Generic Precision Agriculture	IoT characteristics enabling Precision Agriculture
1	Uses multi-year crop growth characteristics in accordance to terrain attributes.	Provides detailed metrics for agricultural monitoring.
2	Usually estimates risk with historical data.	Efficiency in predicting risk and yield with improved decision-making.
3	Data is mostly collected from field using basics such as tractors, sprayers, planters, etc.	Access to necessary data from any device.
4	Uses static indicators (hail, drought, rain, etc.) for the crop management.	Management of applications like irrigation and automated planter controls with better crop protection.
5	Controlled approach by using regular data during the crop cycle.	Identify trends and developing pattern using technologies like AI and ML.
6	Usage of indicators such as soil, field history, resistivity, colouring for the growth prediction.	Usage of UAVs and multi-spectral sensors to determine the health of the plant.
7	Estimates the yield by tracking the crop status (disease level, water stress, and other point indicators).	Lowers the production risk by foreseeing the output of the production and mapping with distribution demand.
8	High level process automation with manual assessment of the growth.	Process automation by using self-commissioning the growth.
9	Incorporating security using field devices and local storage.	Implying data security in the PA by end-to-end encryption.

constraints of IoT edge for transactions.

Various key drivers of IoT in the agriculture industry along with major hurdles in the technology implementation are reviewed by Ayaz et al. [26]. An introduction to the major applications for smart agriculture and underline services is presented at a very high level, including major equipment and technologies. The survey by Jha et al. [21] talks about different automation practices using Deep Learning (DL), AI, and ML. This paper discusses the problems in the agriculture field like water management, crop disease, and the potential solution by using these techniques. It also gives a brief overview of automation in agriculture and proposes a solution for the specific use-case of leaf identification and watering using IoT. Mohammadi et al. [23] discussed on DL, which is an advanced class of ML to facilitate the analytics. It highlights the importance of DL towards data analytics and introduces the underline challenges in the extension for agricultural use-cases. The inclusion of IoT along with emerging technologies needs the adaptation of heterogeneity and interoperability that is covered in the work of Kour et al. [28]. It highlights the development of hardware and software systems, important public and private projects, along with sustainable solutions in PA. However, this survey doesn't cover detailed insights into security and the use of emerging technologies at different layers of IoT. With more interconnected devices, the spatial and temporal variations of data are increasing rapidly, thereby it is vital to have intelligent processing and analysis. One of the ways to achieve this is by using different ML algorithms. Mekonnen et al. [32] did the comprehensive review of AI and ML techniques in WSN based data acquisition for PA.

A. COMPARISON WITH OUR WORK

From the discussion of the state-of-the-art, we can recognize the established inclusion of IoT for precision agriculture. Also, we can identify the technology zones which are covered by the discussed survey papers. For instance, both cloud computation and edge computation play an important aspect in building a solution for PA along with technologies such as ML which is applicable in different layers of IoT. We have seen that in most of the surveys in precision agriculture, authors only consider one technology or provide a high-level overview of utilization of IoT in the same context. It remains vital to study all emerging technologies and their interoperability in one comprehensive survey paper. A single technology can give great results, but a more efficient approach will be achieved by combining most of the discussed technologies towards a common goal.

In this paper, we have undertaken a distinctive discussion of all emerging technologies for PA along with energy efficiency, data management techniques, and potential IoT architectures suitable for precision agriculture. We also discuss the importance and inclusion of energy harvesting and nanotechnology in this domain. This paper extends the discussion on both the simulator and real-time deployment-based approaches. The focus of this work is twofold, first the survey of new technologies that are revolutionizing beyond IoT in the orientation of agriculture. Second, the adaptation of these technologies towards a common multi-disciplinary solution: AgriFusion. The implementation of a multi-disciplinary approach is new to the system, therefore we include literature based on it and eventually propose the architecture along with KPIs.

III. PRECISION AGRICULTURE AND INTERNET OF THINGS

Agriculture is facing ever-increasing pressure to feed the world. This demand and supply gap is getting further burden due to land and water shortage, and the global requirement towards preserving natural resources. IoT helps to fill this gap by using low-cost sensors to send data from farm to the enterprise for minimizing environmental impact and giving benefit for social and working conditions. The illustrative description of an IoT solution for PA is shown in Figure 5. It highlights the role of different layers of IoT and mapped techniques corresponding to the things layer, communication

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

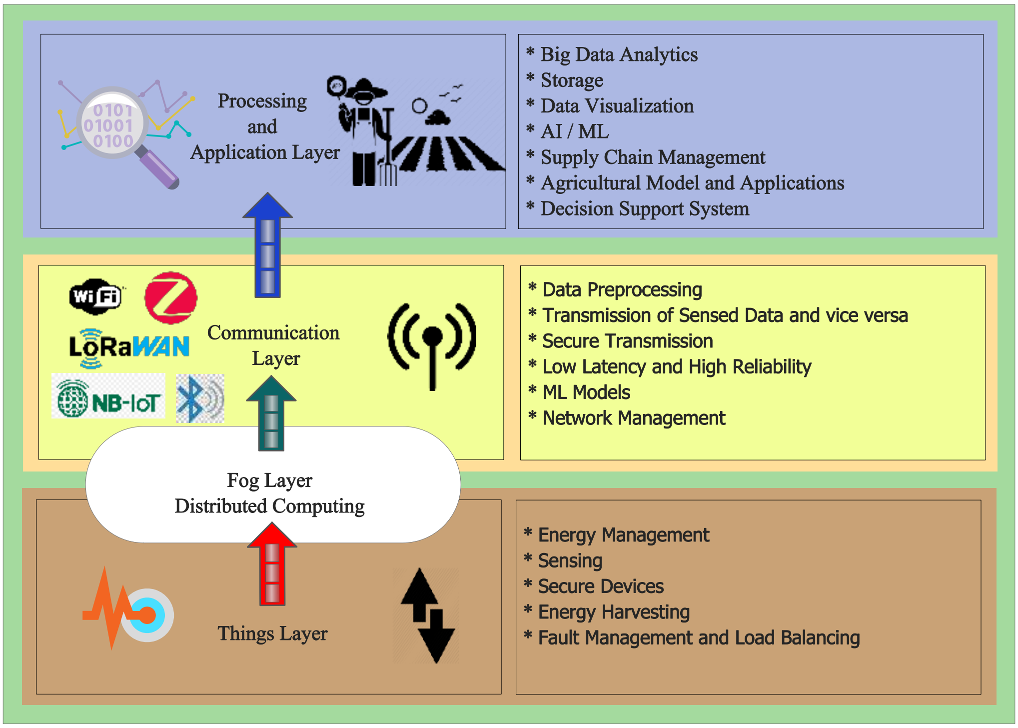

FIGURE 5. The illustrative description showing different techniques at each layer of IoT for precision agriculture.

layer, and application layer. Technology advancements in IoT are helping agricultural businesses to implement PA as one of the major applications of IoT. The origin of PA started in the 90s, with the GPS and satellite provision in the farming vehicles to steer equipment and monitor automatically. The advent of GPS enabled PA to precisely measure many variables, gather data, and create maps of spatial variability. Thereafter, the conjunction of satellite imagery with Variable Rate Technology (VRT) supported the resource distribution. One of the main objectives of the PA is to map farming practices with crop needs, reduce the footprint of farming, and boost economics through more efficient agro-management practices. PA seeks IoT technologies for farm management to ensure the health and productivity of crops along with ensuring soil sustainability. It includes new technologies for higher crop yield and lowering the inputs needed to grow crops. This approach relies upon real-time data from the IoT services along with other relevant information such as equipment and cost. IoT analytics serves the farmer with the data for crop rotation, the optimal time for harvesting, and the management of the farm. Advancement in the IoT technologies with robotic drones and image processing integrated with sensor information guide for future decisions. It searches when, where, or what crop to plant and the ability to identify treatment. In the past, PA was more oriented towards larger operations however with enriching capabilities of IoT (mobile apps, cloud/edge computing, smart sensors, and drones), PA is possible even for family farms. Eventually, PA is one of the main pillars to solve food crisis and demand all over the world. The main objective of the PA is expanding over -

- Identifying suitable crop.
- Increasing crop yield.
- Aligning crops with market demand and trend.
- Capturing relevant data for monitoring the performance.
- Environmental sustainability.
- Proactive response to the disease and climate changes.
- Reducing crop waste.
- Farm security.
- Improving the quality of decision-making for better RoI.

By using, PA farmer gets more metrics for agricultural monitoring, which includes the nature of the nutrients, soil samples, the requirement of fertilizer, and so on. This deeper insight into the field allows the farmer to look into the state of crop, accounting resource utilization, and underlying decisions. The major underlying technologies for PA through IoT are WSNs. It plays an important role in improved decision-making by giving access to real-time data for evaluating distinguished patterns. Also, in identifying potential risks during both the growing and harvesting periods of the crop. This access to farm records is available any time from any device using technologies such as cloud computing. Having the fear and pressure to achieve the yield, most of the farmers tend to go overboard with the use of chemicals, which reduce

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

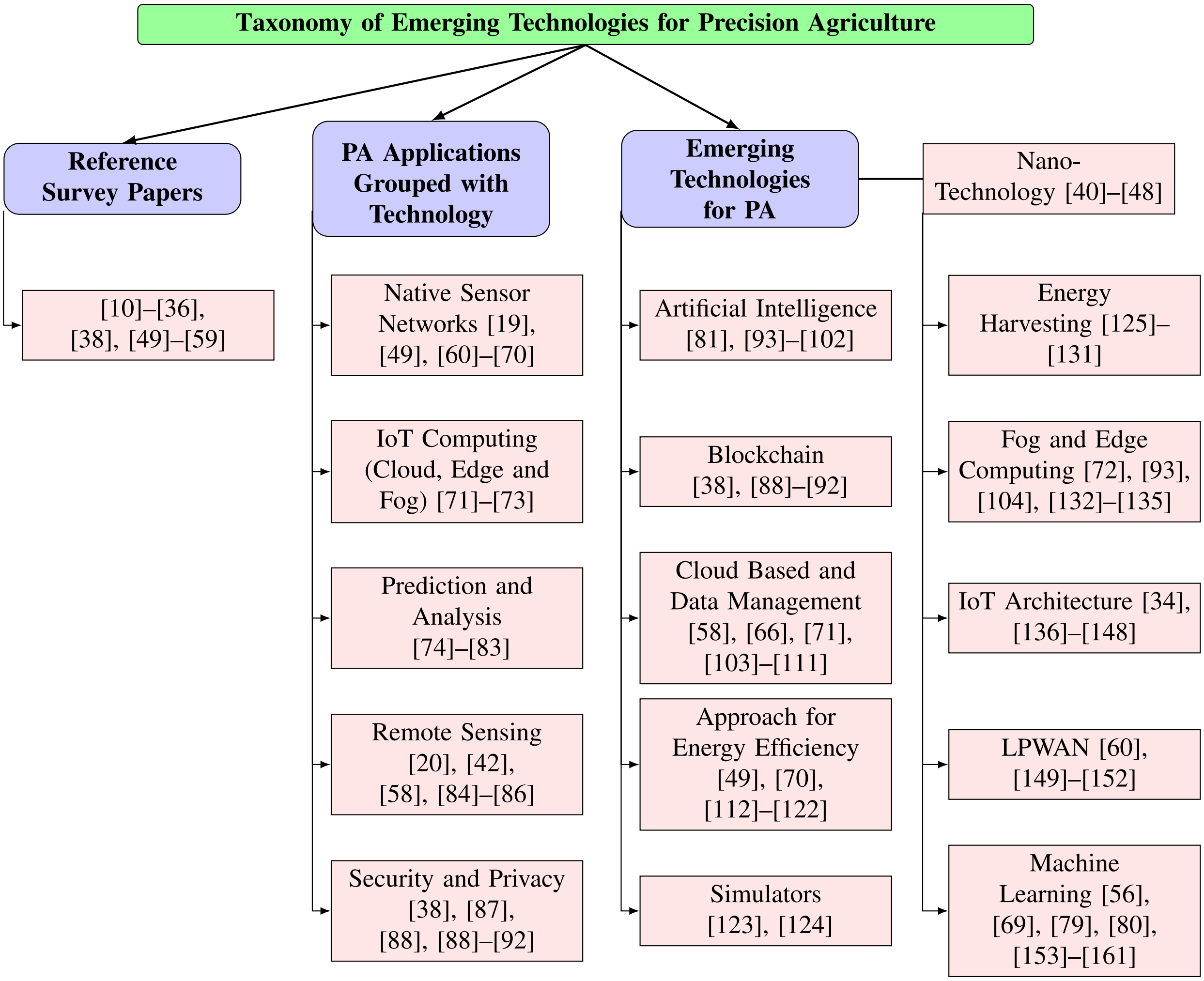

FIGURE 6. The taxonomy of this survey paper.

the environmental sustainability and build up the financial pressure of using expensive chemicals. With the use of IoT services, farmers can administer the requirement and use of chemicals to maintain the high field and low soil pressure. The taxonomy and classification of emerging technologies used in this paper for PA is shown in Figure 6. It consists of all the reference survey papers as used in section II, another set of papers towards PA applications grouped with used technology as discussed in section III-B, and relevant papers for emerging technologies as in section IV.

A. IOT TOOLS AUGMENTING PRECISION AGRICULTURE

Progressive technologies in IoT such as sensors and agriculture management software are the key enablers in data collection and aggregation for PA. They leverage many IoT tools to observe spatial variability and look into insights for an optimized farming process. These tools include remote sensors, VRT, soil sampling, etc. Other technologies like geo-locating a field enable the deep analysis of soil resistivity and information of the previous crop. Long-term monitoring of the field provides information on environmental constants. These point indicators help to identify disease, water stress, and other crop parameters. IoT provisions a predictive and control approach to identify and manage static indicators before plantation itself, such as soil and crop history. Further, during the crop cycle, most of the decisions are based on models using big data, ML, and artificial neural networks. The information system and communication technologies of IoT make farm management more achievable for farmers. A different set of PA applications are commonly used in conjunction with IoT devices, drones, and robots. Other than that, UAVs also help in risk reduction and disaster management by using the fitments such as multispectral and hyperspectral sensors for regulating the stress and health of the plant. The overview of IoT technology applications for PA and their supporting technology along with relevant available literature is shown in Table 3. There has been rapid progress due to the miniaturization of sensors with enhanced capacity and capability to detect different metrics such as

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

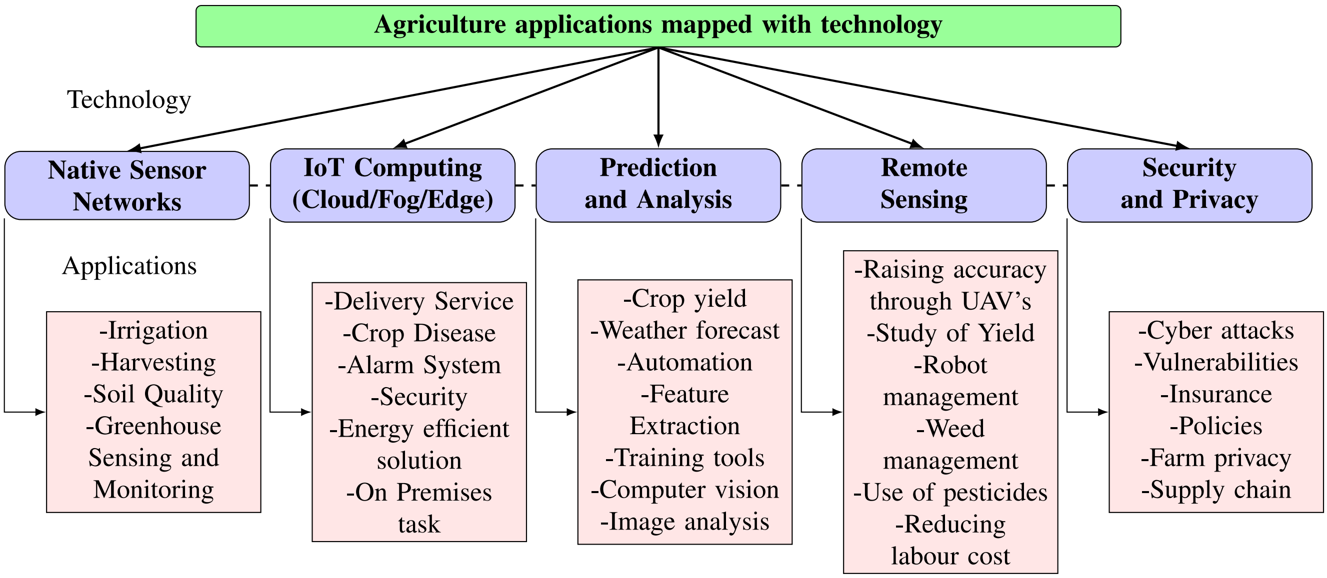

FIGURE 7. Classification of technology and precision agriculture application.

TABLE 3. An overview of IoT technology applications for precision agriculture.

Table Sr. No.	IoT Technology Applications for Precision Agriculture		
	Applications/Use-case	**Objective of the Supporting Technology**	**References**
1	Human-Machine interaction	Reduce chemicals and fuels by automated assistance.	[85], [86], [162]–[164]
2	Access to field data	Facilitate the exchange of data.	[62], [65], [71], [73]
3	Sampling locations	Determining soil fertility, disease etc.	[63], [68], [71], [165]
4	Fertilizer & stress monitoring	Check the state of the crop and requirement.	[64], [166], [167]
5	Sensor Fusion for monitoring	Sensor measurement and multi-layer datasets.	[62], [72], [168]–[170]
6	Learning, predicting, & analytics	Classification, monitoring and analysis.	[74], [78]–[81]
7	Remote sensing	Identify nutrient deficiencies and stresses.	[58], [84], [171]
8	Variable rate application	Accurate mapping of field information.	[42], [61], [63], [67], [172]
9	Harvest monitoring	Localised crop information for harvesting.	[77], [156]
10	Farm management	Solution for monitoring system and data management.	[59], [72], [87], [162]
11	Decision & Risk support system	Decision support for every field operations.	[69], [71], [173]
12	Feature Classification	Feature extraction of crops and weeds.	[75], [76], [82], [83]
13	Unmanned Aerial Vehicles	Field level phenotyping and mgmt.	[20], [85]

biomolecular, electrical, chemical, etc. towards the health of the crop. These data are used for precision farming software to control tools and other management activities. Connectivity protocols are constantly evolving from short rangers (ZigBee or Wi-Fi) to long-range ones (cellular connection, Low-Power Wide-Area Network (LPWAN), and so on) and play a fair share in establishing an IoT solution for intelligent farming. Other location monitoring tools such as satellites are used to monitor water level, crop biomass, etc. The improved accuracy of Global Navigation Satellite System (GNSS) has enabled the expansion of machinery guidance and Controlled Traffic Farming (CTF) systems. These technologies using IoT are effective for the PA which not only benefits the farmers but also the data generated from the farms are further used by policymakers, governments, and other stakeholders.

B. IOT SOLUTIONS FOR PRECISION AGRICULTURE

There is a clear view of the benefits of implementing IoT solutions in agriculture. IoT gives a cohesive picture of the field status along with the multifaceted analysis of crop management. With the help of IoT, farmers can get insights into the state of the farm, weather conditions, and field management. It also helps in reducing the production risks and overall operating cost, which results in reduced resource waste. In advance, the grower gets ample information to plan the yield volumes and plan the distribution strategies assisted by IoT solution. This helps in outlining potential revenues and streamline harvesting as per the lucrative market supply chain demand. In long term, this pattern and trends assist in getting insights on crops, seasonal behavior, disease, and mitigation techniques in advance. IoT for PA furnishes risk management and planning to improve mostly all facets of farm management mainly due to cheaper solutions with more

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

ambitious technologies.

IoT solutions depend upon the farm use-case and derivative applications. Following are the most important and common applications of IoT for PA and can be classified into five prominent groups as depicted in Figure 7. The classification is done by identifying the key technology used by certain applications. There were few overlapping technologies for PA applications, but then the priority is given to the scope and goal of the application.

- Native sensor networks
- IoT computing (Cloud and Edge/Fog)
- Prediction and Analysis
- Remote Sensing (UAVs, Drones, and Robots)
- Security and Privacy

Applications using native sensor networks:

The wireless sensor network is the key enabler of IoT solutions for real-time decision-making towards the applications such as irrigation, harvesting, predicting crop fields, or estimating fertilizer requirements. The low-cost CCD camera is equipped with a sensor network i.e. Wireless Multimedia Sensor Network (WMSN) to meet the requirement of event detection. Over the years sensors are evolved from monitoring environmental factors to leaf compatible wireless sensors based on Radio-Frequency Identification (RFID) technology [64]. These miniature sensors help to monitor water stress levels and environmental impact. They are also equipped with flexible solar cells for energy harvesting. The study by Mat et al. [169] uses WMSN particularly in a greenhouse environment and proves the efficiency of feedback control for irrigation. Shi et al. [62] present the modular set up to adapt the application context of PA and minimize energy consumption. IoT-based smart water management platform plays an important role in the cultivation of crops. The conjunction of several crop factors helps IoT-based irrigation methods to enable precise irrigation as shown in the work of Kamienski et al. [63]. Another way to optimize the solution of smart farms is by using a genetic algorithm where operating conditions are handled as penalty and objective functions [61]. LPWAN solutions are less expensive with high reliability as demonstrated by Singh et al. [49] in leveraging the LoRaWAN solution for greenhouse monitoring. It uses the MQTT communication method for implementing control functions to enhance the development of agricultural IoT [60]. Khoa et al. [68] propose a new technology that is inexpensive and highly efficient by using Lora-based transmission. Adeyemi et al. [67] incorporated adaptive decision-support solution and predictive control approach to enable efficiency in irrigation. Greenhouse environmental monitoring system uses series of sensors to monitor crop growth and process the data in real time [70]. The cloud platforms can process and display the sensor data and provide intelligent decision feedback while supporting scalability [65]. In the greenhouse, it is vital to monitor the plant growth requirements in every phase of the plant. Halim et al. [66] considers this to develop an automated scheduler for each phase and bring down the maintenance and labor cost. For effective monitoring, sometimes sensors and communication devices are partly or completely buried underground. This needs change in the design and implementation of the IoT network architecture [19].

Applications using IoT computing:

The challenge of processing and analyzing the generated data is crucial. In this scenario, the paradigms of IoT and cloud computing exploits the data to manage both the business and environmental performance. Sending all the data to the cloud delves into computational load and latency. Thereby, fog and edge-based computing move the processing abilities closer to the data source [72], which makes it suitable for mission-critical applications. Furthermore, the proximity of computation to the data source maximizes the efficiency of resource allocation, privacy, and service delivery. Omoniwa et al. [174] explores the two-tier fog and reduces the considerable amount of data transmission to the cloud. This reduces the waiting time and allows the management of agricultural land with the clustering mechanism. Further, this computation can be improved by applying data mining algorithms at the edge itself. Computation at the edge helps to identify events like crop disease locally and notify the farmer by SMS [71]. The sensors deployed in the farms need some shade to provide stable and accurate measurements. It is seen in the work of Ferentinos et al. [73] that a spatial representation of temperature and humidity had a difference with higher variability during the day. Thereby, to exploit fully the capability of WSN with computation efficiency, the actuators and sensors need improved design and development as demonstrated by Singh et al. [49].

Applications based upon prediction and analysis:

Agriculture is transforming from only collecting the data to the capability for quick prediction and analysis. Pham et al. [80] highlights digital farming as the incorporation of capabilities required for extensive data collection, computation, and predictive analytics. PA demands proactive anticipation of dysfunctions to realize immediate remedial actions. This can be achieved through a prediction framework by contributing to corrective actions for better crop yield. Santos et al. [79] uses the combination of IoT-driven technology, LoRa along with the ARIMA prediction model. Data mining techniques help to identify behavior patterns from the data collected by the sensor network in the field. The work done by Rodríguez et al. [74] provides a client application tool for the farmers involved in floriculture. This application is integrated with the prediction API and learning algorithms to forecast greenhouse environmental conditions. Computer vision systems are widely employed for producing accurate descriptive data. It is identified in the work by Patrício et al. [81] that intelligent IoT devices can be coupled with AI for automation of field tasks, and integration with agricultural machines. It is essential to have a reliable and updated description of the crop for proper prediction.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

Remote sensing uses satellite imagery that helps to a certain extent but underpins limits in terms of low or moderate resolutions. The deep learning technique assists in imagery refinement to exploit information derived from images. These images can be acquired by airborne multispectral sensors or UAVs. Mazzia et al. [77] proposes a novel satellite imagery refinement framework and uses the same for the case study in a vineyard. The utilization of satellite-driven maps gives a better viewpoint of crop health and stands as a better tool for growers. However, the acquisition of hyperspectral imagery is still a compound challenge, mainly due to high data dimensionality and involved complex information analysis. The review by Dao et al. [82] exhibits the strength long with the limitation of hyperspectral imaging in the context of agricultural applications. A huge amount of data is collected using various means such as sensors, automated tools, and images incorporating remote sensing. The images are then analyzed to develop a model for the prediction of various applications. Features of the images are extracted, segmented, and classified as input to the model. Different techniques help in this process such as neural network, fuzzy logic, and deep learning [75]. Semantic segmentation of the aerial farm images remains a challenge, to solve this Chiu et al. [78] proposes a solution i.e. Agriculture-vision. It annotates nine types of field anomaly patterns and proposes an effective model for pattern recognition. Further to this, precise weed and crop classification can be achieved by using deep learning. Fawakherji et al. [76] used a robot to train and label pixel-wise segmentation of data sets in a different context. Another pixel-based classification approach of the crop was done by Bosilj et al. [83]. It coupled the classification technique with morphology-based segmentation without any computation overhead and was able to provide descriptors with better resolution.

Applications based upon remote sensing and UAVs:

Modern technology development across remote sensing techniques uses UAVs that assist in raising accuracy, cover large land areas, and enable accuracy of the observation for PA. The major challenge in the operation of the crop monitoring system is the long-distance communication from sensor nodes and the appropriate usage of routing algorithms aligned with energy consumption. The viability of the network for efficient services needs security and privacy as the crucial parameters. Network size and transmission media are the functions of architectural components based on IoT technologies and application use-case. Triantafyllou et al. [58] propose architectural components for PA in cooperation with energy-saving schemes. It covers a case study of yield using remote sensing and depicts spatial variability to adopt site-specific management. However, it limits the scope by not including heterogeneous data and technologies that can be used in remote sensing for depicting correlations in yield and inputs. The use of UAVs extends the capability of remote sensing for the applications like irrigation, use of pesticides, weed management, crop disease management, and many others. The use of drones makes agricultural applications very specific and interesting. Review by Boursianis et al. [20] enfold the use of multiple Unmanned Aerial System (UAS) to accomplish composite agricultural missions by cooperating and using techniques like particle swarm optimization and genetic algorithm. Agricultural production needs a lot of input from natural capital that requires the economic feasibility of employing human workers for different tasks. As a consequence, a robotic application is required to react dynamically to the highly variable environment. In this context, robot for PA needs to be configurable, incorporate safety measures, adhere to the sensitivity of the crop, and follow the general principle of service. Marinoudi et al. [86] outlines the constraints and inherent relationship of using robotics in agriculture. However, there is room for improvement to manage and coordinate between fleets of the robots aligned with task alongside incorporating techniques such as image analysis, ML, and AI [163].

Applications building security and privacy in PA:

On-field sensors and devices connect synergistically to provide an efficient farming solution. The use of heterogeneous devices and connectivity has exposed vulnerabilities and cyber-attacks in the agricultural domain. These attacks vary from exploiting autonomous vehicles (UAVs, tractors, etc.) and flooding the farms to over sprinkling of pesticides resulting in an unsafe farming environment. Large coordinated attacks have the potential to bring down the economy of a country by targeting the agriculture sector. A report [175] extensively elaborates various threats in PA and the demand for research in this domain. With the ubiquitous use of IoT technologies, it is crucial to build and follow the compliance and regulation for protecting the solutions. Security in PA is paramount, a minor security breach has the potential to affect the entire food supply chain. The standards can be enforced by regulations drawn by the country or by following cyber-security operation standards drafted by an individual/local authority. Further, the food supply chain can have cyber insurance policies but with the integration of AI and smart applications, it is even more difficult to quantify and predict the involved cyber risk [88]. Several contributions have been made to designing and optimizing the cyber-physical systems for agriculture. The ongoing trend is in using a combination of technologies to empower cyber-security. In the same context, Selmani et al. [87] uses solar photovoltaic water systems to guarantee a bidirectional communication in the greenhouse.

IV. EMERGING TECHNOLOGIES AND APPROACHES FOR PRECISION AGRICULTURE

The Smart agricultural solutions are designed based upon the target crop and required application. Therefore, to match these requirements, authors have proposed work using different technologies and frameworks. This section reviews application areas and organizes them by their used technology. We can identify the IoT technologies based on their usage

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

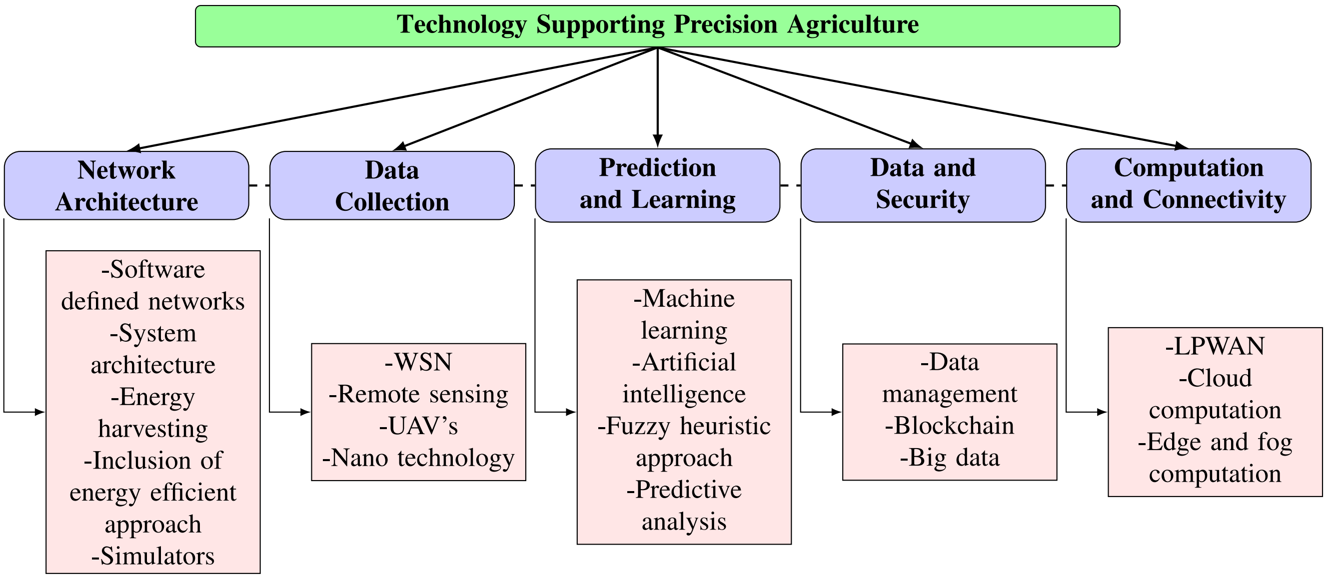

FIGURE 8. Classification of multidisciplinary approach for precision agriculture.

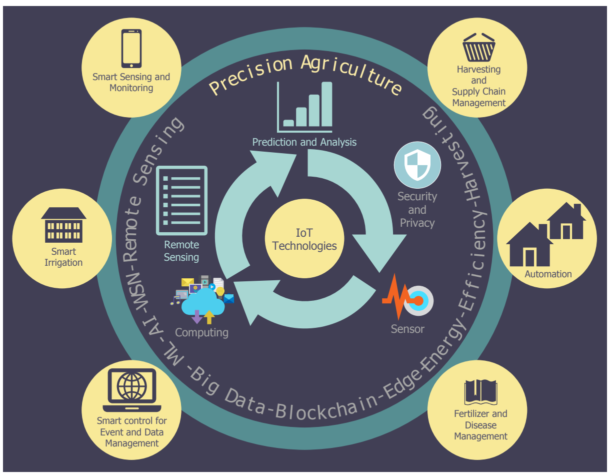

FIGURE 9. Precision agriculture applications using different technologies.

in different applications for PA. Figure 9 illustrates some of these PA applications mapped with emerging technologies diagrammatically. The outer circle shows different PA applications and use-cases such as smart irrigation, harvesting, and disease management. The inner-circle shows emerging technologies that support IoT solutions in achieving the PA goals. IoT leverages different technologies for analysis, prediction, and computing for PA. These technologies can be classified into the following broad areas as shown in Figure 8. For the classification of multidisciplinary technologies, the focused scope of the technology is classified under the umbrella of the following categories:

(A) Network Architecture
(B) Data Collection
(C) Prediction and Learning
(D) Data and Security
(E) Computation and Connectivity

A. NETWORK ARCHITECTURE

The management of network architecture requires network configuration, maintenance, and performance management of the deployed devices in the field. The three-tier architecture and the involved interactions of the IoT system for PA are shown in Figure 10. It depicts the deployment of sensors in the crop area and knowledge extraction in the next layer for a decision support system. The last layer is for the user to handle and plan applications such as auto-guidance, command, and response, etc. Data is gathered from the crop area, following that knowledge is extracted and then used by the end-user. The real-time gathered information in the crop area helps manage nutrients, pesticides, and water for the plants. At the next level of knowledge extraction, data goes through the distribution platform for performing different actions. The last level is for the user to provide command, response, and visualization of crop data. The design of the network architecture needs to be adaptable towards events and problems likely to occur. The architecture for PA solution depends upon the topology, required Quality of Service (QoS), energy, and security management along with low maintenance in real-time.

Software Defined Networks:

A software-defined network segregates the control plane from the data plane in the deployed architecture. There is a logically centralized controller that controls and manages the behavior of the network. As per the instructions from the controller, network devices (sensors and other on-field devices) forward and process the data. This gives the provision to manage network configuration globally by integrating APIs between the data, control, and application planes. By

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

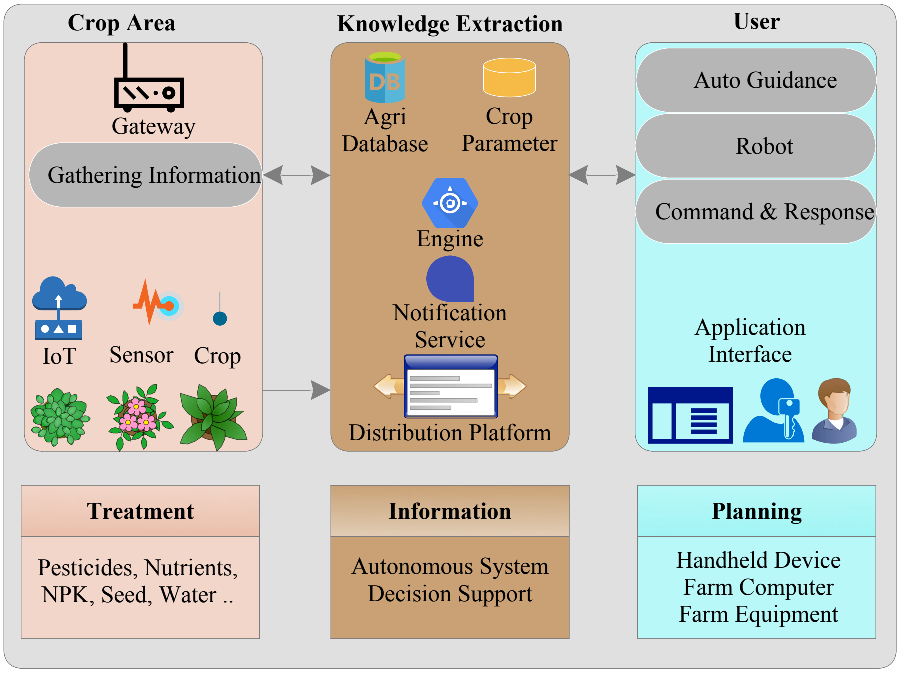

FIGURE 10. The Interaction between different Layers of IoT Solution for Precision Agriculture. The illustration shows the utilization of an IoT solution at crop area for treatment, knowledge extraction for decision support, and planning for the end user.

facilitating the flow control, network architecture becomes flexible, offering potential benefits specifically in energy and configuration management.Integration of SDN with PA based sensor deployment can help in managing efficient resource allocation and performance. It provides a global view of the entire network management that is crucial for vast crop fields. Network deployment for the agriculture use-case needs the regular management of network topology, QoS, and remaining energy with the changing crop cycle. This can be achieved centrally in the control plane and management/integration of technologies at different levels of architecture. Integration of SDN paradigm with agricultural solutions has introduced simplicity and flexibility in the network, suitable for the farmer to farmer solution. SDN based vehicular sensor network architecture helps in gaining performance by making the data plane efficient and simple. In farms, there can be unstable wireless links that may lead to connection failures. Hence, the vehicular network can bring reliability between controller and switches as the topology of sensor networks in agriculture can easily change and adapt to the old rules. In the same context, Huang et al. [176] build SDN based agricultural vehicular sensor networks based on extended open vswitch. Ndiaye et al. [177] reviews the different techniques available for SDN-based network management. It expresses that the major challenge of implementing SDN is in enabling and integrating different technologies while encountering the cost and nature of the application. The work done by Alonso et al. [178] proposes a double Deep-Q [179] learning approach using edge IoT architecture to manage virtual data flows in SDN. It reduces the implementation cost and allows dynamic management of the resources.

System Architecture:

The system architecture should have the capability to handle enormous data received from heterogeneous devices, that should be processed appropriately and effectively. The implementation of architectures depends on the complexity of the system and the intended requirement. The design of the architecture greatly rests on the performance functions such as reliability, security, data throughput, and physical environment [147]. Internet of Underground Things (IOUT) consists of sensors and communication devices partly or entirely below the ground. To facilitate seamless integration of the complex network with the underground sensors, sensing technology, and communication mechanism has to be identified accordingly [19]. The network requires low power consumption and management cost, in this scope Deniz et al. [136] designed the sensor node employing BLE communication. However, this is limited to a perspective of having larger connectivity coverage in a big greenhouse. In contrast, Codeluppi et al. [144] presents LoRaWAN based smart farming modular IoT Architecture: LoRaFarM for improving and customizing the management of farms. The review by Ray et al. [138], highlights architecture capabilities related to the tool, technology, and methodology along with possible research opportunities. In addition, Lytos et al. [148] covers the state of the art for agriculture architectures including

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

big data both in research and commercial space. Vasisht et al. [180] propose an end-to-end IoT platform for agriculture: FarmBeats, that enables seamless data collection from various sensors, cameras, and drones. Farm management information systems are continuously developed in many farming solutions. An architecture design method for farming and deriving the customized application from the requirement analysis is provided by Koksal et al. [143]. This approach is illustrated using two case studies for wheat production and smart greenhouses in Turkey. A major challenge in intelligent farm management is the limited availability of the energy source at the edge of the network. The network needs an energy-efficient framework to adapt and collect the data upon any change. An energy-efficient algorithm to guarantee the transmission rate with minimal energy consumption is proposed by Lerdsuwan et al. [145]. The architecture based on power networks is undergoing a fundamental shift, Mahmud et al. [141] contribute in this context by accumulating and summarizing the significant ideas for controlling, optimizing, and managing distributed energy resources.

Intelligent farming is one of the crucial applications of IoT solutions, providing a computational platform for imperative interactions between machine-to-machine and the sensor network. Nobrega et al. [146] reviews the recent developments and evaluates the gateway performance for the IoT network. To realize accurate sensing, more devices are getting added to the network for instance, Xue-Fen et al. [142] presented a hybrid node with the inclusion of smartphones for distributed agricultural service. In addition, Pastor et al. [137] uses edge computing along with the ubiquitous sensor network to monitor the greenhouse. Another set of architecture uses distributed computing for precision agriculture. This user-centric design model is used to facilitate the decision-making and for optimal usage of resources. Architecture based on different decision trees [34] is used to automate the installation and support the farmers. It includes layered communication and processing at edge or fog nodes as per the interconnected functionalities. This work can be further extended by using ML and AI as shown by Andrew et al. [139] to revamp the results.

Energy Harvesting:

Several energy-efficient schemes have been introduced to tackle the limitation of the limited battery capacity of the sensors. An alternative method is to do the energy harvesting using different ambient sources such as solar, wind, vibration, raindrops, and wireless power transfer from different methodologies. Ambient energy is harvested to supply the rechargeable sensor nodes with power to enhance the lifetime of the network. The review by Jawad et al. [181] discusses the possible harvesting mechanism for the agricultural use case. Solar energy based on photo-voltaic provides a cost-effective solution for agriculture [127]. Wireless power transfer significantly contributes to transmitting electromagnetic energy between two devices. UAVs can help to extend the battery lifetime of the deployed sensors through the harvesting of electromagnetic radiation in an agricultural field. In the survey: The digitization of Agriculture Bacco et al. [126], authors focus on the technical challenges mapped with cost, resistance to environmental conditions, and energy efficiency. The targeted solution to this problem is through the inclusion of energy harvesting techniques for gaining reliability and prolonging the lifetime of the network, which can bring down the maintenance cost as well. Another method for energy harvesting is by converting bipolar thermal gradients to electrical energy. Sigrist et al. [131] introduced harvesting architecture along with a novel low power circuit to rectify the small bipolar voltages utilizing ambient conditions. Still, there remains a remarkable difference between the power consumption rate and the harvested energy. Energy harvesting can be done from multiple resources at varied time as per the availability. Gleonec et al. [130] presents the sensor network powered by energy harvesting from multiple resources simultaneously and calculates the energy budget of the sensor over different tasks. A comprehensive review by Sherazi et al. [129] highlights the trend of current research and aims at minimizing energy consumption. It does not look into performance metrics aligned with energy harvesting. There are solutions like solar-powered node [128] to monitor agricultural production whose performance can be further investigated while using a different set of emerging technologies.

Energy Efficient Approach:

Energy efficiency can be gained by employing various techniques during different phases such as deployment, radio connectivity, edge computing, and by applying algorithms for fault management and load balancing. Singh et al. [182] demonstrated the road map for achieving an energy-efficient solution in the greenhouse. Several power reduction techniques such as radio optimization, data mitigation, and sleep/wake strategies were discussed in the review paper by Jawad et al. [181]. The energy efficiency of the network can gain momentum by including efficient energy harvesting systems on top of energy prediction models to maximize its benefits [183]. Transferring data from sensor nodes to the sink uses routing protocol, this should meet few parameters such as rate of energy consumption, robustness, convergence, and scalability in the field [184]. By choosing an energy-efficient routing scheme, the overall energy consumption of the network can be minimized. A substantial amount of the energy is exhausted in the transmission of data [152]. Thereby, it is crucial to send the data only when it is necessary and avoid retransmissions. Lakshmi et al. [114] discusses the routing protocol that can be used in the context of IoT-based precision agriculture. Obtaining low power consumption and high reliability are crucial factors for the development and design of the sensor network. The factors such as transmission frequency of the sensed data and configuration of radio modules impact directly the energy consumption of the node. Therefore, it is crucial to choose a communication protocol with less power consumption rate. Srbinovska et al. [121]

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

propose low maintenance and low-cost sensor network for greenhouse crop production by retaining the communication module in an ideal state for most of the time.

There are a lot of contributions in the scope of energy efficiency and energy management techniques [185] towards building an IoT solution in agriculture. Saraswat et al. [116] deployed an energy-efficient WSN network for the PA monitoring system. However, this work does not consider the interference caused by the crop itself in the real-time propagation of the signal. Dhall et al. [112] covered this challenge by proposing a duty cycling algorithm for special events such as cloudy weather, etc. It offers an efficient path selection based on the residual energy of the node however, results are simulation-based that may differ in the real world. On top of the duty cycle, a sleep/wake scheme is proposed named as SWORD [118] for energy efficiency in PA. Another simulation done by Yang et al. [115] demonstrates that by the addition of backup routing nodes the connectivity can be further increased. It uses ZigBee based sensor network for monitoring a greenhouse over an NS2 network simulator and predicted the path using Received Signal Strength Indication (RSSI). Another similar use case to determine the growth of the greenhouse in an energy-efficient way is shown in [70]. The IoT platform consists of heterogeneous components and their interactions such as multiple WSN gateways, databases, and connectivity. Kuo et al. [168] uses IEEE 802.15.4e time-slotted channel hopping protocol for multi-hop, energy-efficient, and collision-free transmissions and [186] uses time-synchronization for lowering the cost of LoRa solutions securely. Saqib et al. [113] propose an approach for collecting data for a fully automated agricultural system. This model can be used for any wide-area information monitoring system as it emphasizes low cost and covers larger distances rather than data speed in the agricultural context. Variable sampling interval helps in gaining energy efficiency while using heterogeneous devices on the field. For example, Hamouda et al. [120], proposes a system to monitor different parameters for respective agricultural activities. Sensor node sampling is done for each area independently to sense the soil temperature and humidity. The dynamic power management approach for estimating soil parameters is given in [187], to establish an adaptive balance between nutrient estimation and energy consumption. An extension for the energy efficiency as the next-generation architecture is proposed by Nguyen et al. [93]. This is done by including AI and DL to reduce the power consumption of the platform. Also, techniques such as fuzzy-based clustering [117] for transmitting sensed data can be beneficial in minimizing the energy consumption and in improving the network lifetime.

Simulators:

Simulators are used to evaluate the performance of different wireless technologies, along with performance parameters intrinsic to different protocols. Each network has its acquisition and underlines processing of the data, connectivity, and the QoS. The networks can show different behavior for energy consumption while sending a huge amount of information to the enterprise or cloud. Several case studies and solutions are implemented on a simulator like NS2, before actual realization on the farms. This enables the study of different performance metrics before the actual deployment. In the same context, simulator: LWS [124] is designed for wireless underground sensor networks to incorporate soil path loss for agriculture applications. It demonstrates the performance of LoRaWAN with different node densities, coverage, and depth of the sensor nodes. Soto et al. [123] compared the performance metrics of ZigBee, LoRa, Bluetooth, and WiFi. However, the accuracy of simulation results is not always identical to a real-life deployment, but only gives a relative glance from the actual results.

B. DATA COLLECTION

Data collection is an important element from data acquisition to processing and analysis. Data is collected through several means such as WSN, remote sensing, and likewise. Different techniques and approaches for data collection are discussed below-

Wireless Sensor Networks:

Advancement in sensor technology has an indispensable impact in fetching plants, the environment, and other information required for an application. Sensor networks have acted as a key player for the deployment of a variety of applications for precision agriculture. Crop field monitoring for detecting environmental conditions, monitoring disease, and other sets of network applications represent huge benefits for the farmers. It can be classified into terrestrial WSN and wireless underground sensor networks [57]. The design and performance of sensor networks depend upon deployment strategy, localization, synchronization, characteristics of wireless radio, and security measures [188]. Optimal WSN solutions need to spend minimal power consumption during all phases of acquisition, sampling, and performing efficient communication. The architecture of a typical wireless sensor node constitutes perception, network, and application layers. The sensor node detects physical phenomena and uses various methods of routing protocol, intelligently based approaches, etc. [189] to forward the data to the gateway or cloud for further analysis and representation. Ahmed et al. [190] analyses MAC and routing solutions to achieve better throughput, performance, and energy. It proposes a computing solution to save the bandwidth of the network with lesser delay. Efficient communication technology is the basis for an effective WSN solution. It ranges from short, medium, to long-distance wireless communication. It is identified in the work by Feng et al. [191] that NB-IoT, ZigBee, and LoRaWAN are the most appropriate communication technologies for agriculture applications. Madushanki et al. [192] gives an overview of different wireless technologies ranging from high to lower frequency that has been used in respective percentages for PA. The current penetration of WSN in agriculture along with potential value and challenges are presented in [18]. There

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

has been a substantial increase in the use of greenhouse agriculture globally. It is highly dependent upon the construction and the material used to build the greenhouse to maintain the ambient conditions for plant growth. With the use of WSN, greenhouses are no more versatile and have in-depth information on the climatic conditions. The main challenge in the greenhouse is the requirement of extensive supervision to maintain ambient conditions for plant growth and attain high yield and crop quality. There can be several sensor systems in regard to some performance parameters [193] for different PA applications. Different types of sensors used in the greenhouse along with the range of communication protocols are discussed in [194]. Hamouda et al. [195], a greenhouse smart management system (GSMS) is developed to monitor, control the cooling, and have smart irrigation in the greenhouse. A prototype of optimized WSN is developed by Ferentinos et al. [73] to investigate special variations of environmental conditions in the greenhouse and shows high variation of temperature and humidity. Implementation of WSN in greenhouses still has open challenges such as the limited lifetime of the network, optimization of transmission intervals, and sampling technique. Thereby, balancing the trade-off between cost, coverage, and handling the layout to manage communication limitation is of important consideration [196]. Another recent advancement in WSN is the intelligent collaboration with UAVs for large-scale and geographically distributed deployment [197].

Remote Sensing:

Developing more productive agricultural solutions is triggered by remote control and sensing techniques using different types of sensors and UAVs. These UAVs help in improving accuracy with efficient monitoring of the fields, including field and aerial perspective. Remote sensing involves different categories of intelligent input control systems such as GPS, GIS, UAV tracking, and advanced sensors. Out of these, sensors are the basis for a decision support system in remote sensing [58]. All collected data from the sensors is stored in the remote server through APIs for different features as per the architecture. Further, all the services are mounted in the cloud to provide remote access from any location. Based on the solution-oriented architecture, farmers can remotely interact with the tools and services deployed in the farm for applications ranging from planting to harvesting. Pallavi et al. [198] proposed a remote sensing application for the greenhouse to control different environmental parameters. It demonstrates the remote management of parameters like light, temperature, and soil moisture for greenhouse monitoring.

Unmanned Aerial System:

UASs are instrumental from the start of the crop, during its different growing phases, and finally harvesting and completing the supply chain. In the start, they are used to producing precise maps to plan planting, soil analysis, and later used for irrigation and fertilizer management. They can scan the field and spray the right amount of pesticides at the designated point. The sensors mounted on the UAVs help to detect crop health and improve conditions locally. UASs assist in soil and field analysis that becomes the input for the farmers to start planting. Thereafter, UASs help in spraying and crop monitoring. The dataset generated from the UASs multispectral sensors helps in the classification and training of the NNs [77]. Nowadays, the use of UAVs is expanding and is growing with the combination of 3D reconstruction modeling techniques. The paper [20], claims IoT and UAS as two prominent technologies that have the potential to transform agriculture. Further, UAS based solutions can be enriched with the inclusion of ML techniques.

Nano-technology:

Advancement in nanotechnology in materials and biomass is improving PA applications. Nanoscale carriers do the delivery of fertilizers and pesticides at a micro and specific level. Another advancement is in the development of nanofabrication that enables to get insights into plant cells and other disease-related issues. Conversion of products into nano form enhances the delivery, growth regulators, and other physiochemical properties. Nanotechnology is used in several ways ranging from fertilizers, crop monitoring, and the packing involved in supply chain management [42]. The development of nano fertilizers and nano pesticides helps to gain sustainability [48] as it does not impact the soil decontamination but promotes growth and productivity. Prasad et al. [46] highlights the current challenges of sustainability that can be solved with the improvement of nanotechnology. Sensors used in agriculture applications are also converging towards nanoscale dimensions with the help of electrochemical nanosensors, wireless nanosensors, and nanobarcode technology. Usage of these nanomaterials also implies potential risk with the level of exposure. The safety practices and regulatory consensus for responsible use of nanotechnology in agriculture are shown in [47].

C. PREDICTION AND LEARNING

Prediction and learning algorithm involves knowledge classification from the dataset. Major technologies contributing towards prediction and learning are discussed here:

Machine Learning:

ML is creating new opportunities for data-intensive science applications such as crop management, yield prediction, disease detection, and maintaining crop quality. By using ML over sensor data, intelligent programs can provide decision support and recommendations to the farmers. It involves a learning process from the training data to perform a task. The performance of this task is measured by the objectives set in designing KPI metrics that are derived from experience over time. The role of ML in PA solutions is shown in Figure 11. It shows a different set of ML-powered applications mapped with the categorization of its capability. ML is classified into supervised and unsupervised categories. In supervised

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

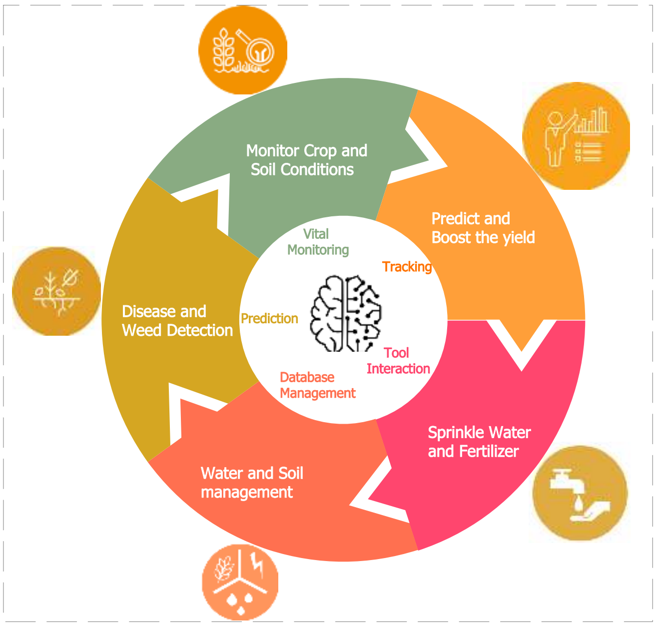

FIGURE 11. Role of machine learning in precision agriculture solutions. The figure illustrates application mapped with the domain use-case of ML.

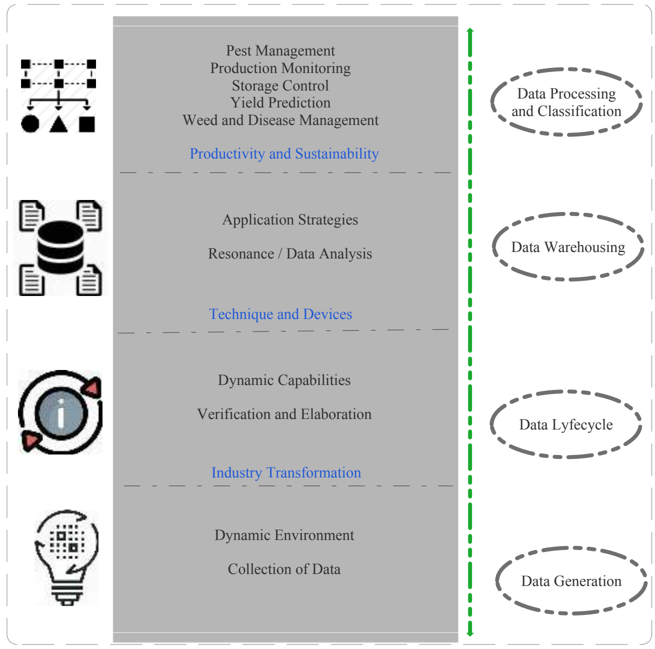

FIGURE 12. Role of artificial intelligence in precision agriculture. The figure shows the application of AI at various stages of data cycle for incorporating capabilities.

learning, a generalized mapping is done with input and the objectives set for output. It predicts the missing outputs using a trained model and available data set. However, in unsupervised learning, the goal is to discover patterns with no distinction between over training and test datasets. There are a lot of ML learning models in both categories to seek as much information as possible before applying the classification model. To encourage further progress in promoting the efficiency of ML, several data sets and classifications are presented such as CropDeep [158]. Liakos et al. [157] reviews several articles on ML in agriculture. The findings in this paper state that the majority of the paper related to ML are in crop management and others are mostly for soil, and water management. Another review paper by Garadi et al. [56] lists the issues and challenges of using ML and DL methods to develop an end-to-end security solution. ML is also used to avoid water stress and unpleasant impact through patterns and association in the growth of plant [155].

Artificial Intelligence:

Artificial Intelligence is an emerging technology that utilizes learning capabilities to provide multidimensional agro-intelligent solutions. The AI algorithms can do most of the manual work, reducing cost and time. The paper [100] showed that the AI algorithm performs better than the manual growers in the greenhouse by enabling automation and decision-making. The role of AI at different layers of the IoT solution is shown in Figure 12. Most of the use-cases of AI are for increasing productivity and reducing labor cost [102]. AI is used to model different applications such as weed management and processing volumes of available data through sensing. It can be applied in different segments of the solution architecture. AI in embedded sensing provisions running Neural Networks (NN) locally for decision-making near the sensed data itself. Edge AI enables energy efficiency by sending only meaningful data to the cloud enterprise. Aggregating advanced AI like deep belief networks with computer vision opens opportunities for featuring different insights of the sensed data.

Fuzzy and Heuristic Approach:

Fuzzy logic enables the reasoning capabilities in the agricultural solution. It helps in controlling tools and devices used in the farms for quick automated decision-making. It provides the capability of dealing with uncertainties with acceptable reasoning. It has basic four modules as membership functions. First, it creates a fuzzy set with the received input and then uses its knowledge base to apply if-then rules to simulate the reasoning process. Finally, it comes up with a crisp value by transforming the fuzzy set. Low-cost fuzzy logic to control nonlinear systems in the greenhouse is demonstrated by Algarín et al. [199] and its contribution in energy efficiency for sensor network is presented by Maurya et al. [200].

Prediction based Approach:

The predictive technique uses exploratory data analysis and other regression models to effectively predict agriculture yield or disease. Prediction techniques enhance the productivity of the field by providing recommendations and alerts at the local level. This minimizes the expenses and contributes

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

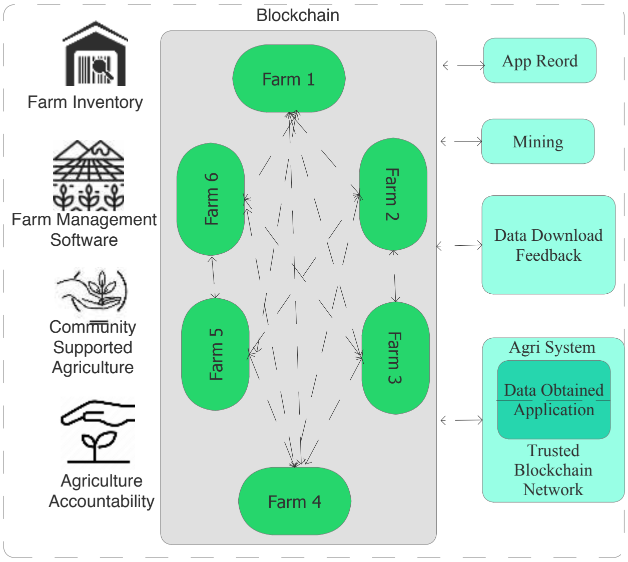

FIGURE 13. Blockchain use-case for precision agriculture.

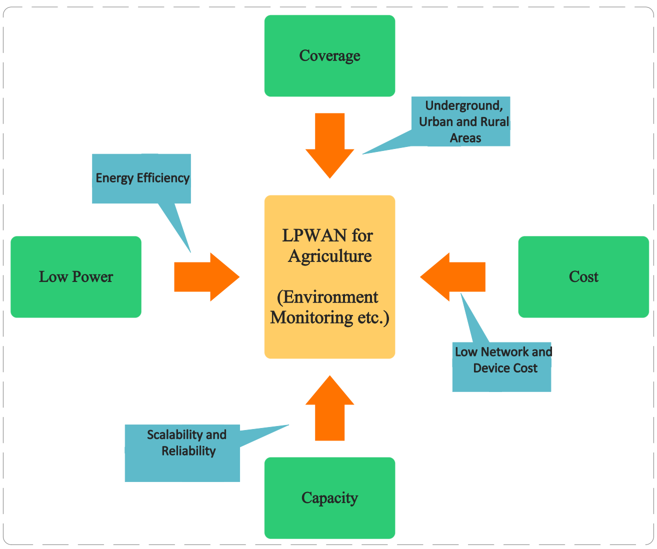

FIGURE 14. LPWAN features favouring agriculture applications.

to sustainability. It integrates production recommendations and maximizes agricultural planning for profitability. Also, it enables the grower to perform predictably rather than reactively. There are different solutions and techniques for prediction, such as utilizing ML for crop yield and forecasting climate status. The work by Chen et al. [150] proposes a predictive soil farming solution: AgriTalk, for outdoor soil cultivation.

D. DATA AND SECURITY

Data collection practices are improving, which presents multiple benefits in agriculture. It encourages better management of decisions by referring to old data. Having this sample data, there comes a challenge of sharing, securing, and owning the data for a secure utilization of the application.

Data Management:

It provides a basis for software applications in performing operations and knowledge mining. It enables the storage and representation of data collected from heterogeneous devices to provide real-time support. The crucial criteria for data management are energy efficiency that directly negates the overall cost. The service for facilitating information management is done by integrating multiple applications securely. The main challenge in the management of data is 'what to keep where'. There are techniques like context-aware approach [108] to facilitate automation and a controlled environment in the greenhouse. This data management system relies on a sensor network to provide decision support for different applications.

Blockchain:

In the agricultural solution, the main challenges lie in providing data security and privacy. With the adaptation of IoT-based agriculture, an adversary may use a data injection attack, which demands more secure communication. An enormous amount of spatial data gets generated from heterogeneous devices, which opens up the risk of unauthorized access causing the potential threat. Data attacks are possible from the cloud or edge data leakage [88]. Other attacks like side-channel attacks, third party attacks, data fabrication attacks and likewise affect the supply chain and networking of the solution. Thereby, the solution demands threat modeling against privacy, authentication, availability, integrity, and confidentiality [38]. The blockchain-based solution is used in architecture management for eliminating the risk of including a third party. One of the example use-cases of farm management using blockchain is shown in Figure 13. Different sets of farms participate in trusted agricultural applications and likewise. There are a set of farms that participate in the blockchain cluster for shared services and enhanced security. As shown, farms 1-6 are in the same trusted blockchain network and have the application record for applications such as farm management, community supported agriculture, farm inventory, and its accountability. The blockchain platform enforces policies for access control to add transparency and scalability to the network. Lin et al. [89] proposed a blockchain infrastructure for agricultural systems and focus on the challenges of blockchain to be tackled with the adaptation and implementation in real-world e-agriculture solutions.

Big Data:

A wide variety of data is captured from farms that are diverse and are of massive scale. Big data encompasses this information to provide real-time agriculture operations, decisions, and business models. It represents the set of information characterized by a huge volume and variety of

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

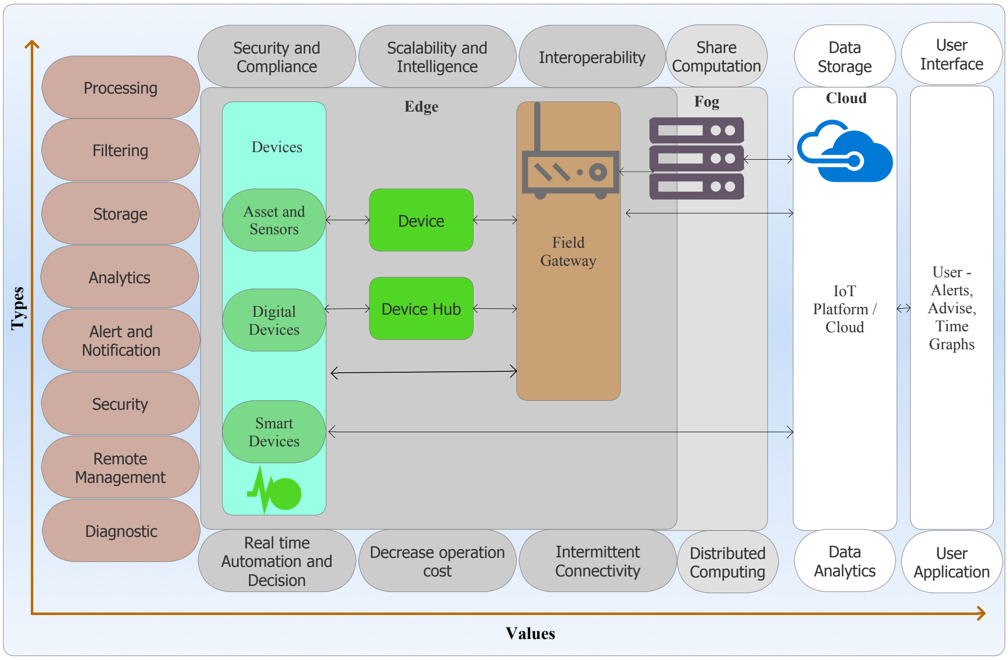

FIGURE 15. Edge, Fog and Cloud implementation. The 'Y' Axis represents the types of Implementation and the 'X' axis represents the added value to the solution.

data to reveal insights. Opportunities in big data applications for agriculture include models to tackle crop risk, sensor deployment, data analysis, and predictive modeling [11]. Big data provides granular data to the farmers regarding rainfall patterns, fertilizer requirements, and more. This way, farmers can adhere to government regulations and guidelines to avoid the overuse of chemicals. Further, harvesting big data helps in achieving supply chain efficiencies by provisioning tracking and routing.

E. COMPUTATION AND CONNECTIVITY

Current IoT technologies are using cellular, short-range, and LPWAN networks to enable PA use cases. The cost of sensors and hardware is dropping drastically, enabling solution providers to offer off-the-shelf low-cost and customized solutions. However, these simpler solutions need to unlock the further potential of connectivity and computation to bring in low latency, high resiliency, and scalable network specific to agriculture solutions.

Low Power Wide Area Networks:

LPWAN acts as a connectivity enabler to support agriculture applications, complementing both short and cellular communication. LPWANs are the perfect solution for PA applications. It provides features such as energy efficiency, long-range, and low costs that are favorable for PA applications as shown in Figure 14. A variety of technologies exist in both licensed and unlicensed RF bands. Given remote locations of agricultural land, these long-range and low-power technologies such as LoRaWAN are helpful in better coverage and long operation time of devices. By retrofitting traditional networks with LPWAN networks, vast distance farms can be monitored efficiently. It provides a connectivity link range of multiple kilometers to support scalability. The work done by Singh et al. [152] on analysis of LPWAN, concludes that LoRaWAN is more energy-efficient as compared to other technologies such as Sigfox and NB-IoT. Various solutions used LoRaWAN for PA such as [49] for greenhouse monitoring. Wu et al. [124] focuses specifically on LoRaWAN to incorporate the soil path loss model and proposes more fine-tuning in modulation schemes to yield better results. Another, work by Fraga-Lamas et al. [201] proposes LoRaWAN based architecture for the smart irrigation system.

Cloud, Fog and Edge computation:

Data acquisition procedures have evolved to a level where addressing and managing data is possible over any layer from edge/fog to cloud. Fog/Edge-based computation enables distributed architecture for service provisioning and acting locally, while cloud-based solutions help in mission-critical solutions. Edge and fog computing brings the computation closer to the end-users. This brings down the cost of sending all data to the cloud and minimizes the considerable latency. Cloud computing aims at sharing the maximum computational load to enable devices near the edge to be less costly and encourages a longer battery life. The implementation of edge, fog, and cloud computation is shown in Figure 15. On the 'Y' axis it shows the type of computation that can be done and on the 'X' axis it shows the values that can be brought in with the respective usage in the solution. The work by Guardo et al. [72] proposes a fog based framework for PA to balance the computational load. A different set of nodes and

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

devices with separate capabilities are taken for the different tasks. Few nodes perform data filtering and aggregation, and other nodes do actuation management. In the paper by Singh et al. [152], it is demonstrated that most of the energy is consumed in transmission so minimizing the frequency of communication itself can increase the lifetime of the sensor node. This can be achieved by performing edge computing near the sensed data. In most of the solutions, data is sampled at every fixed interval of time, irrespective of the change in information or event. All the data are forwarded to the cloud for processing and analysis. This adds to the transmission cost on top of the data mining cost in the cloud. There can be lightweight ML algorithms to support edge computation for sending only meaningful information and can be further managed by keeping intermediate fog nodes.

V. IOT SOLUTIONS FOR PRECISION AGRICULTURE

Agricultural solutions are immensely getting popular and being adopted by the relevant users. Table 4 highlights some commercially available solutions and companies with their expertise on the application domain and used technology for PA. This list of companies was selected by searching and reading for trending precision agriculture companies in the last three years for example by referring to the top ten companies to watch in 2019 [204]. A large set of companies work towards improving yield and automating farms. Others, mostly work in data management, artificially lighting the crop, and identifying stress and nutrients during the crop cycle for disease and weed management. It is seen that lately, companies have started aggregating multiple technologies in building an application. Solutions such as UAVs on top of WSN with remote sensing for aerial data collection and data science following AI over big data are seen to be an emerging trend. From the connectivity point of view, most of the companies are building solutions using LoRaWAN and NB-IoT as connectivity enablers. Companies like Intel and Microsoft are working in bringing down the cost of embedded systems, along with making a collaboration of heterogeneous devices and technologies for an effective solution. There has been a shift in the focus of companies. Initially, it was a separate solution track from biological and technological domain companies. However, with time now the focus is moved from consideration of biological or technological space to solution-oriented goals infusing a mix of domains and technology for a better solution.

VI. KEY PERFORMANCE INDICATORS IN IOT FOR PRECISION AGRICULTURE

KPIs enable a quantitative comparison of different parameters involved in the operational plans. The generalization of KPI starts from pre-deployment using simulations till the final deployment. For PA applications, optimal KPIs are designed to manage levels. One of the key benefits of using KPIs is to provide a comparison set of alternative solutions to visualize the performance aligned with the requirement. A range of KPIs can be calculated to define the operational plan, configuration plan, and final solution plan. One of the challenges, while planning the solution for PA is to define the optimal solution as per the requirement and available resources. Often, the final objective has overlapped performance criteria such as reducing cost, minimizing energy consumption, increasing yield, or others. Some of these criteria are conflicting and need a trade-off between them. For instance, more messages are expected from the sensors for implementing ML and at the same time, a longer life is expected from the sensors. Thereby, at the end KPIs are calculated and criteria are selected from a user acceptance point of view. Figure 17 shows the performance metrics of IoT for PA. It depicts different performance metrics to control processes and information systems for an agricultural monitoring solution. The illustrated performance metrics can be selected as per the application requirement. For instance, in the environmental sensing application, energy and cost can be the potential KPI. The proposed design process of the KPIs for any PA application is demonstrated in Figure 16. It has three layers - the Requirement process, Data sourcing process, and Design Process that are closely coupled to each other. Firstly, in the requirement process, different level of analysis is done over factors such as risk analysis, data acceptance rate, and economic impact. The requirement is gathered and mapped with the productivity, resources, and other categories for acceptance. Thereafter, finalized details from these acts as an input to the data sourcing process for the identification and selection of data. At this stage, data is collected, analyzed, stored, and selected to define the KPI goals. Application-specific, KPI goals are defined among the agro-partners by identifying different parameters and measured variables. At this level itself, KPI list are formed with the acceptance value. Finally, design and KPI goals are derived in the design process. Here, the KPI goals are set as per the application requirement. This is a sequential step approach from collecting requirements to the design finalization. The example of designing KPIs is demonstrated in Figure 19, it keeps energy consumption as the major KPI criteria for a PA application. Initially, the requirements of the use-case are defined and different power requirements are identified. Thereafter, since energy consumption is an important KPI so analysis is done for all the possible factors impacting energy consumption. Input from the analysis is mapped with appropriate power requirements to satisfy and manage KPIs. The solution architecture for developing agriculture management KPIs are shown in Figure 18. The objectives for the PA application are defined based on measurements, that are further derived from indicators and defined in the requirement phase. Performance metrics are calculated on the deployment of sensors that can be latency, coverage, or battery life of the sensor nodes. The trade-off between performance metrics and connectivity requirements is adjusted as per the application priorities. Accordingly, changes are given as feedback to indicators. The KPI solution is designed to be - SMART i.e. specific, measurable, attainable, relevant, and time specific. As illustrated in the Fig 18, the network metrics

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

TABLE 4. Industrial solutions for precision agriculture and respective focused technology [202], [203]

Sr. No.	Company/Solution	Focus Domain	Focus Technology
1	Mothive	Right time to harvest, predict disease, improve yield and automate farms	ML, AI, Cloud Architecture
2	CropX	Adaptive irrigation software with integrated wireless sensors	Soil Sensors, Aerial Imagery, Hydraulic Models
3	Ceres Imaging	An aerial spectral imagery for water and fertilizer application.	High-resolution multispectral imagery.
4	Arable	Irrigation management tool, weather station and monitor crop.	NB-IoT, LTE-M, Soil Moisture Probes, Mobile application.
5	Gamaya	Detection of disease, stress level and pests.	Collect drone and satellite-based remote sensing imagery.
6	AgriData	Asset tracking system and predict yield, harvesting time and disease.	Features and mapping capabilities for data management.
7	Agrowatcher	Identify water stress and disease using computer vision.	Computer-vision technology and multispectral imaging.
8	AgEagle	Drone enabled imaging and analysis.	Aerial imagery collection and analytics solutions.
9	PrecisionHawk	Aerial data collection and management using autonomous UAV.	Aerial mapping using Drones.
10	Aker Technologies	Computer vision and biometric sensors to measure fertility issues.	RGB and multispectral based crop health imagery.
11	Monsanto	Data science and digital tools for agriculture.	AI, Remote sensors, satellites, and UAVs.
12	Syngenta	Counter threats and ensure nutritious and affordable food	AI
13	Gavilon	Local knowledge, market intelligence and global distribution network	Crop nutrients analysis and distribution.
14	AeroFarms	Data driven indoor vertical farming.	LED Lighting, Predictive analysis, ML
15	Farmobile	Uses Agronomic and machine data to inform insights.	Data management
16	Surna	Climate control equipment and management	Controlled climate systems.
17	Freight Farms	IoT farm management solution	Building farm inside shipping container.
18	Voeks Inc	Hydroponic and Farm designs	PRIVA and ARGUS monitoring systems.
19	HelioSpectra	Lighting needs based on natural light simulations	Sensors and Lights.
20	FMC Agricultural Solutions	Arc™ farm intelligence platform to predict pest.	ML, AI with Crop models.
21	Skycrops	Early diagnosis and reaction.	AI and Robots
22	Farmable	Efficiently track, monitor and record operations	Application and database of farm records.
23	Azotic Technologies	Technology for nitrogen fixation in crops.	N-Fix technology
24	Gamaya	Provides crop monitoring system by using ultra-compact sensors.	Big data, Remote Sensing
25	ECF Farmsystems	Provides heating, lightning, and irrigation solution.	Sensors, Remote maintenance and analysis.
26	Agrivi	Incorporates information about weather, fields and equipment and provides management software.	Analytic and data management
27	PlantLab	Radical new plant logic : Growing plants with less resources.	Plant Production Units
28	CropX	Automatic irrigation system including WSN and mobile application.	Decision making, pattern analysis, LoRaWAN and Cellular connectivity, Sensor deployment.
29	Proagrica, part of RELX Group	Farms management software	Data management solution
30	Raven Applied Technology	Field, machine and application controls	Cloud based data management
31	Terrasharp	Yield forecast, disease detection and monitoring.	Remote sensing, drones and satellite data.
32	Microsoft	Data coupled with the farmer's knowledge.	AI, Edge computing, ML, Drones, Computer Vision
33	IBM	Watson decision to improve harvesting and crop quality.	AI and Cloud technology
34	Intel	Soil testing and monitoring solution.	ML algorithms, FPGAs, Cloud platform, Drones, Blockchain, Sensors, LoRaWAN

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

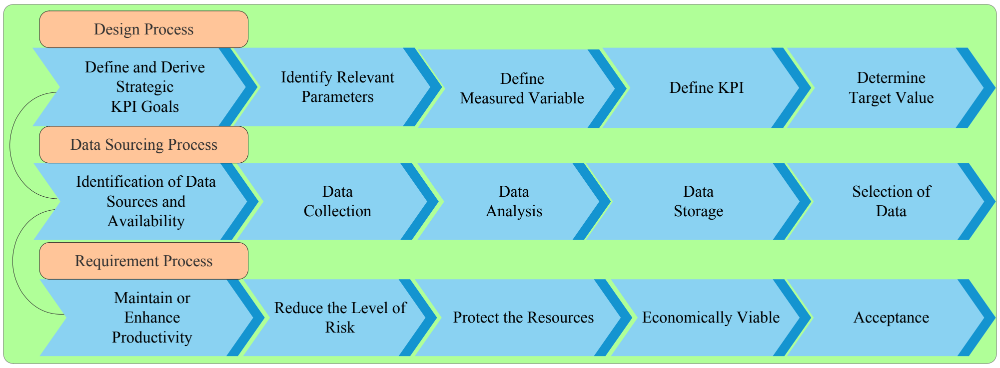

FIGURE 16. Design process for the key performance indicators.

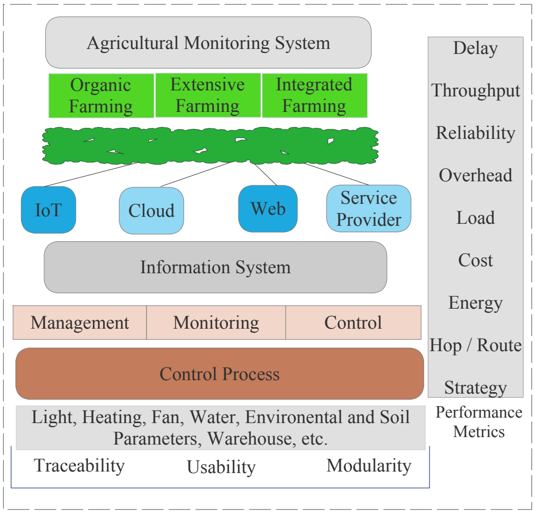

FIGURE 17. Performance metrics of IoT solution for precision agriculture.

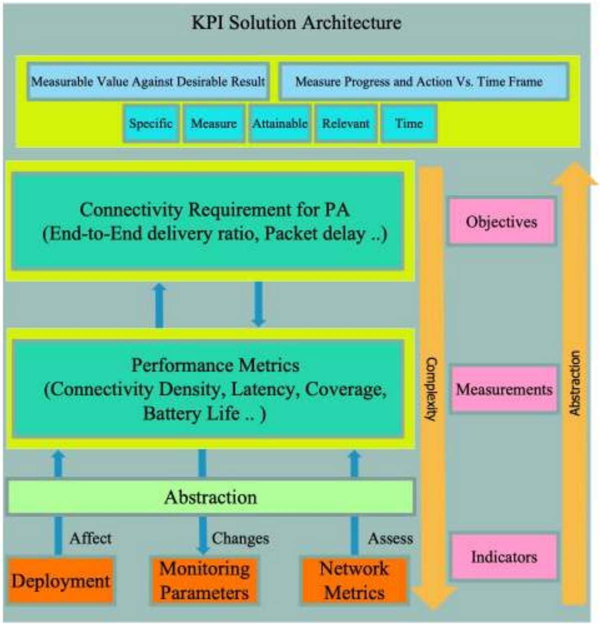

FIGURE 18. Solution architecture for key performance indicators showing the relation between objectives, measurements, and indicators for precision agriculture.

and deployment gets affected by the change in monitoring parameters. These parameters help to fulfill the objective of the solution.

VII. AGRIFUSION: MULTIDISCIPLINARY APPROACH IN IOT

The future of precision agriculture depends on advancements in IoT technologies. However, it still faces a challenge due to the lack of adaptive architecture that can deal with the interoperability of heterogeneous components and technologies. An efficiently designed architecture can pave the way for deploying IoT solutions for smart farming. Most of the architectural models were based only on static nodes, one technology, no prediction mechanism, and limited contribution towards energy saving. Some data-driven architectures did not include data security at all. For instance, the architecture by Ferrández-Pastor et al. [34] illustrates the communication level with functionality in IoT. It does not cover the

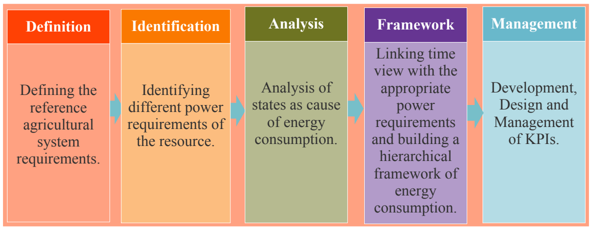

FIGURE 19. Step approach for managing energy consumption related KPIs.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

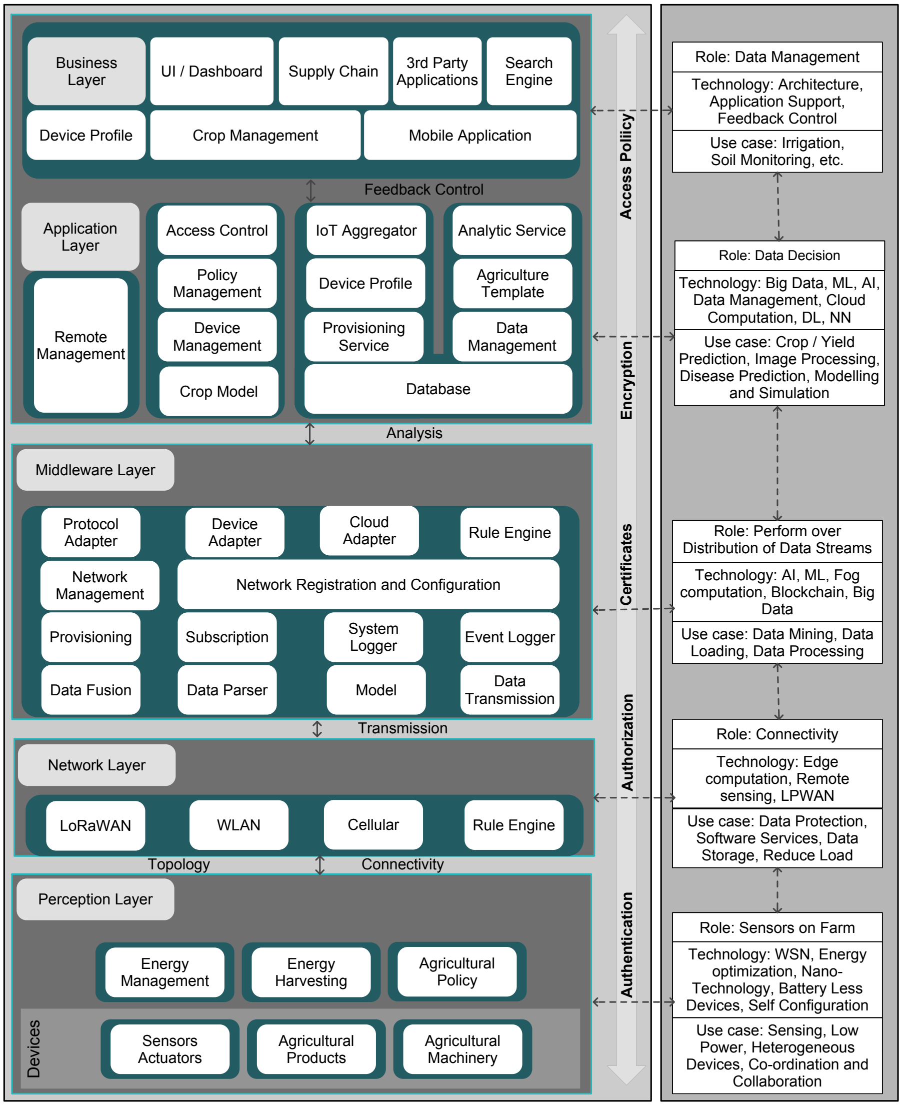

FIGURE 20. AgriFusion: Architecture with the fusion of multidisciplinary technologies for precision agriculture.

integration or plugins of different technology at respective levels. The architectural model for PA should engage multi-disciplinary technologies and their capabilities to provide an enriched solution.

Based on the available solutions and engagement of different technologies in the literature survey, we proposed a five-layer IoT architecture - Agri-Fusion. The Figure 20, has three vertical scopes (1) Services involved in each layer, (2) Architecture with main components for PA, (3) and Inclusion of respective technology and use-case mapped with all vertical scopes. In the architecture, the lower layer is the perception layer, which consists of sensors and other sensing devices. The sensed information is collected and forwarded to the upper layer by the embedded device. Since there are heterogeneous devices, so they need coordination and collaboration among them for energy efficiency and reliable data acquisition. The ongoing research in this layer focuses on the usage of nano-technology in developing sensors, and making them extremely low power or rather battery-less with self-managing capabilities. The network layer acts as a transmission medium for various kinds of information collected from the perception layer. It also directs the perception layer for different changes in a control scenario. This layer needs good data protection, storage, and reduced load techniques. For agricultural use-case, LPWANs are among the best suitable connectivity enablers with added value from edge computing. This layer sends data to the middleware layer to perform data mining, data loading, and data processing. It enables a different set of services for the application as illustrated in the Fig 20. Also, it simplifies the management of new services or devices in the solution. Integration of blockchain, AI, ML, or big data helps to make this layer more intelligent and includes automation for the different use-case. Further, the platform layer is responsible for decision-making and data processing for knowledge extraction. Various categories of algorithms and models are based here for different applications such as

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

crop yield prediction, image processing, and simulation activities. The decision in this layer is derived by using ML, AI, cloud computation along with other recent technologies such as DL and NN. The core responsibility of data management in this layer helps in setting up agriculture templates and services for the application. The application layer provides value and utility to the users through intelligent platforms and systems for different applications like - early alarm systems, environmental monitoring, and many more. It is responsible to manage the control and feedback from the user to the perception layer. AgriFusion architecture envisions the applicability and utilization of different technologies along with their integration at different layers of an IoT architecture. This can be easily adapted to any PA solution by selecting the technologies at each layer and aligning them with application objectives.

VIII. FUTURE RESEARCH DIRECTIONS AND OPEN ISSUES

The development of low-cost sensors and their adaptability is envisioned to be seamless. The evolution of prediction techniques such as AI and ML is gravitating to the research domain. There is a necessity for low power or even batteryless network with reliable connectivity. The data collected needs real-time handling of data using big data and accurate algorithms. The overall performance of the system can be measured with the KPIs that can be inculcated with technology-specific future research directions. Figure 21 shows the future PA applications and open issues based on the reviewed literature. There is immense opportunity for the development and enhancements of current technologies focused on different PA use-cases. The research community has contributed well to the innovation and key technologies in PA but it remains very specific to technology or application. Thereby, there is a scope of advancements in binding different technology domains for a more precise and common solution. The network architecture needs openness of the platforms and better management for the adaptation of different technologies. Data collection strategies can exploit the potential collaboration of real-time feedback and detection of anomalies. As the data will grow so the heterogeneous data sources, thereby prescribing relevant data are required from the edge network. The applications that need heavy computational and low latency can be supported by edge and fog computing. Services involved for PA need to be coupled with an intelligent prediction and analytics approach to adapt uncertainty and dynamic factors. Crop wastage can be avoided by performing the forecasting of harvesting and mapping it with the supply chain requirements. This will require smart service subscriptions and privacy-oriented blockchain solutions. The battery is one of the major constraints for both environment and running the network. This demands future PA applications to have battery-less devices with self-management capabilities.

A. OPEN ISSUES BASED ON LITERATURE REVIEW

Based on analysis of the literature, few challenges are identified as an obstacle for adaptation and building PA applications. One of the biggest challenges is the acceptance of the PA solution for both small and large-scale farmers. It is seen that local farmers are a bit skeptical in acceptance of the IoT solution, considering privacy and security as the major issue. Thereby, privacy needs to be regulated and policies should be transparent to maintain the trust of the farmers. With the increase of different types of devices, device management, coordination, and collaboration have become of utmost importance. The base network for any PA application needs the capability of self-management and configuration to handle cost and enable a quick decision support system. To keep the solution cost-effective for the farmers, devices are of mostly average computational power. Existing ML algorithms need comparatively heavy computation power and storage. So, there is a need for lightweight ML and AI algorithms with enriched automation techniques. Open issues based on literature review for different emerging technologies are shown in Figure 21. It illustrates the open issues in different technology segments such as big data, ML, security, and remote sensing.

B. PRECISION AGRICULTURE ERA 4.0; 5.0 TO NEW GENERATION 6.0

The consensus to industrialize agriculture needs the adaptation of PA and quantitative approach for combining collaboration between humans and machinery. Farming 4.0 needs telecommunication infrastructure and the ability to utilize data for agricultural supply chain [205]. Digital farming or Farming 4.0 uses a data-based digital system to enhance the knowledge of growers. These farms incorporate AI and UAVs to get more insights which are termed as Agriculture 5.0 [206]. Integration of robots and AI in the farm helps to complete a certain task in a faster way than humans. Next-generation of agriculture 6.0 will use deep training data set to help early-stage farmers as well. The evolution of agriculture is pointing the equipment makers to bring in technological advancements through robots, UASs, and likewise next-generation farm machines. The future towards Agriculture 6.0 will target achieving both production and environmental goals. One of the crucial aspects in achieving this is by fusion of multidisciplinary technologies, as depicted in this survey paper.

IX. CONCLUSION

PA is becoming the absolute necessity to manage global food requirements. With the help of sensors, IoT collects vital information from the farms and forwards it to the cloud application over a secure network. The collected data is processed using different technologies such as big data, AI, and ML to look for any inconsistencies and use them for decision-making. Different applications such as a disease forecast alert system help to tackle uncertainties for the farmers. It forms the basis of Agriculture 5.0, the new set of frameworks for smart agriculture.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

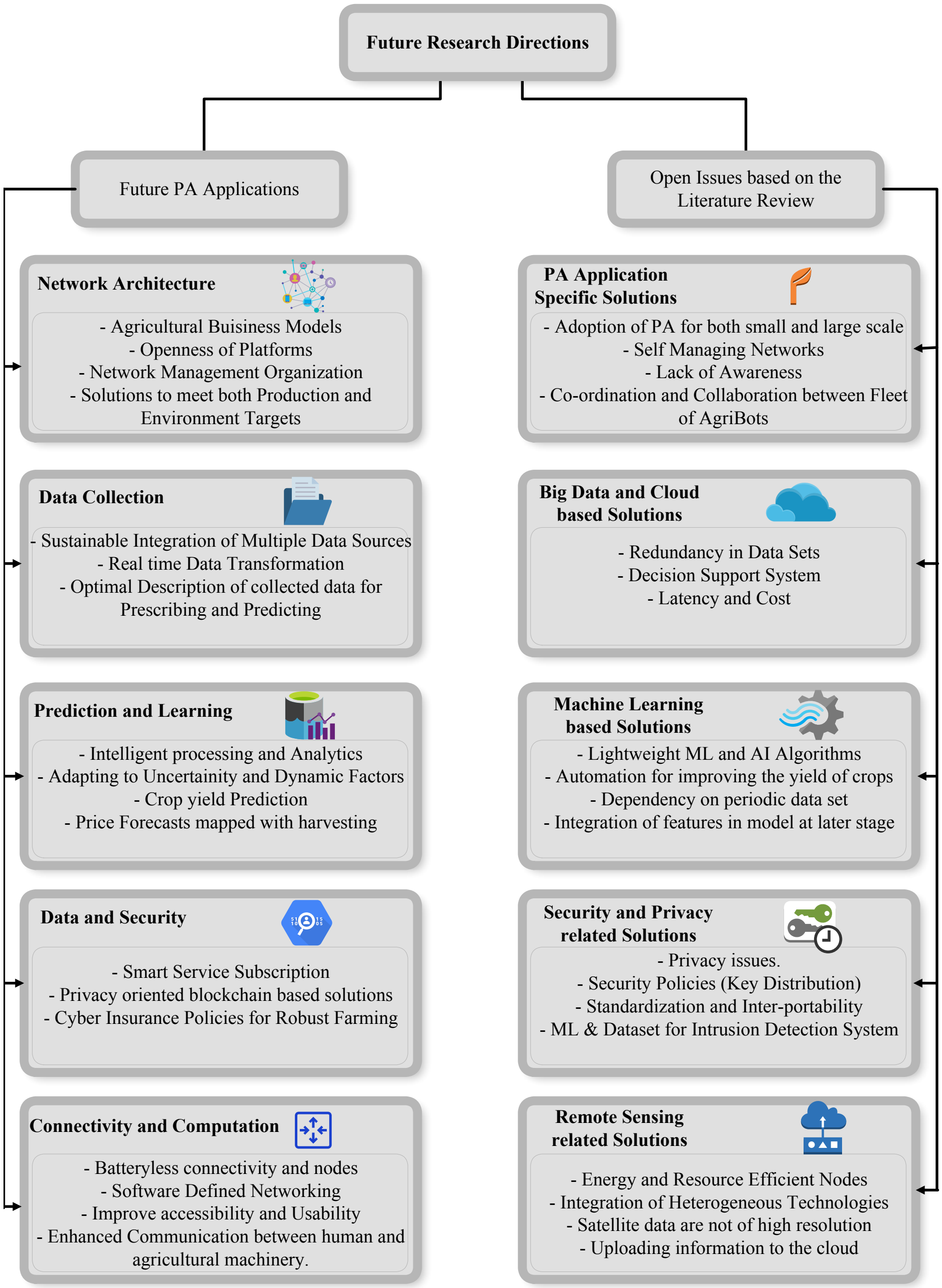

FIGURE 21. Future research directions and open issues in precision agriculture.

This work reviews emerging technologies that power PA solutions. Several new technologies are being employed by different solutions to make PA more energy-efficient, adaptable, and precise. Solution architectures use different computation paradigms at edge, fog, and cloud for data processing. These architectures are further supported by ML, AI, big data, SDN, and other new technologies like nano-technology and blockchains. The capabilities of remote sensing using UAVs are exploited in several use-cases to achieve optimal networks with high coverage and performance. Edge computing has a major role in sharing and bringing the computation load closer to the source of data. This enhances reliability and reduces the latency of the network by avoiding traffic over the cloud. For agriculture applications such as monitoring greenhouse, it is vital to control the tools and devices with minimal time in processing the data. Another layer of fog computing brings in capabilities such as storage, security, and processing the data at the farm for a quicker response such as smart irrigation and alert system. Large data sets are produced from the farm that needs continuous analysis, big data provides an analytics framework to identify crucial information for prediction and application management. Sen-

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

sors nodes are mostly energy constraints and act as the core of the sensing platform. Energy harvesting through ambient sources such as sun, wind, and raindrops can empower sensor nodes to have longer battery life and service to the network. Other energy efficiency techniques have a trade-off between power consumption and its implementation. Securing information and delivery is another perspective for bringing reliability to the network. Blockchain enhances this security element with data storage capabilities to bring transparency and secure services to the network. SDN adds flexibility to the network by separating data and management planes for resource utilization and bringing down the operational cost. Nano-technology is driving the utilization of fertilizers and tackling the plant stress level to the nanoscale. Overall, these technologies are the driving force for tackling the need for PA with environmental sustainability that can be further accelerated by using a multidisciplinary approach towards a common PA application.

Based on the comprehensive survey, we proposed an IoT solution architecture: AgriFusion, where the applications and multidisciplinary emerging technologies are mapped to each layer of IoT for the efficient use-case. This will enable the integration of multidisciplinary technologies towards the common endmost application goal. Many challenges have been identified, which are the KPIs for the application. We proposed the step approach for designing the KPI for an application along with the architecture to reflect the dependency and interactions deriving the KPIs. Based on different technologies, future research directions are identified in this paper. These technologies are pushing precision agriculture to a paradigm shift and opening new avenues of opportunities. By close analysis of the literature and industrial trends, it is clear that the adoption of PA is exponentially growing and will help in feeding the world.

REFERENCES

[1] M. Hatton, "The iot in 2030," IoT.Business.News, Tech. Rep., May 20, 2020.

[2] M. Research, "Agriculture iot market - global forecast to 2027," Meticulous-Research-v4061, Tech. Rep., October, 2020.

[3] "Towards a definition of the internet of things (iot)," 2015.

[4] Harvard Business Review, "Global demand for food is rising. can we meet it?" 2021, [Online; accessed 8-March-2021]. [Online]. Available: https://hbr.org/2016/04/global-demand-for-food-is-rising-can-we-meet-it

[5] euractiv, "One french farmer commits suicide every two days, survey says," 2018, [Online; accessed 8-March-2021]. [Online]. Available: https://www.euractiv.com/section/agriculture-food/news/one-french-farmer-commits-suicide-every-two-days-survey-says/

[6] I. Zambon, M. Cecchini, G. Egidi, M. Saporito, and A. Colantoni, "Revolution 4.0: Industry vs. agriculture in a future development for smes," *Processes*, vol. 7, p. 36, 01 2019.

[7] eitfood, "Sustainably feeding the world in 2050: Are efficiency and equity the answer?" 2019.

[8] U. W. FAO, IFAD and W. 2020, "The state of food security and nutrition in the world 2020," 2020.

[9] BBC, "The high-tech farming revolution," BBC World News: London, UK, Tech. Rep., 2019.

[10] M. Ge, H. Bangui, and B. Buhnova, "Big Data for Internet of Things: A Survey," *Future Generation Computer Systems*, vol. 87, pp. 601–614, 2018. [Online]. Available: https://doi.org/10.1016/j.future.2018.04.053

[11] S. Wolfert, L. Ge, C. Verdouw, and M. J. Bogaardt, "Big Data in Smart Farming – A review," *Agricultural Systems*, vol. 153, pp. 69–80, 2017. [Online]. Available: http://dx.doi.org/10.1016/j.agsy.2017.01.023

[12] P. Radoglou-Grammatikis, P. Sarigiannidis, T. Lagkas, and I. Moscholios, "A compilation of UAV applications for precision agriculture," *Computer Networks*, vol. 172, no. February, p. 107148, 2020. [Online]. Available: https://doi.org/10.1016/j.comnet.2020.107148

[13] A. Kamilaris, A. Kartakoullis, and F. X. Prenafeta-Boldú, "A review on the practice of big data analysis in agriculture," *Computers and Electronics in Agriculture*, vol. 143, no. September, pp. 23–37, 2017. [Online]. Available: https://doi.org/10.1016/j.compag.2017.09.037

[14] A. Khanna and S. Kaur, "Evolution of Internet of Things (IoT) and its significant impact in the field of Precision Agriculture," *Computers and Electronics in Agriculture*, vol. 157, no. December 2018, pp. 218–231, 2019.

[15] M. Torky and A. E. Hassanein, "Integrating blockchain and the internet of things in precision agriculture: Analysis, opportunities, and challenges," *Computers and Electronics in Agriculture*, vol. 178, no. November 2019, p. 105476, 2020. [Online]. Available: https://doi.org/10.1016/j.compag.2020.105476

[16] I. Cisternas, I. Velásquez, A. Caro, and A. Rodríguez, "Systematic literature review of implementations of precision agriculture," *Computers and Electronics in Agriculture*, vol. 176, no. July, p. 105626, 2020. [Online]. Available: https://doi.org/10.1016/j.compag.2020.105626

[17] D. Glaroudis, A. Iossifides, and P. Chatzimisios, "Survey, comparison and research challenges of IoT application protocols for smart farming," *Computer Networks*, vol. 168, p. 107037, 2020. [Online]. Available: https://doi.org/10.1016/j.comnet.2019.107037

[18] A. Tzounis, N. Katsoulas, T. Bartzanas, and C. Kittas, "Internet of Things in agriculture, recent advances and future challenges," *Biosystems Engineering*, vol. 164, pp. 31–48, 2017. [Online]. Available: https://doi.org/10.1016/j.biosystemseng.2017.09.007

[19] M. C. Vuran, A. Salam, R. Wong, and S. Irmak, "Internet of underground things in precision agriculture: Architecture and technology aspects," *Ad Hoc Networks*, vol. 81, pp. 160–173, 2018. [Online]. Available: https://doi.org/10.1016/j.adhoc.2018.07.017

[20] A. D. Boursianis, M. S. Papadopoulou, P. Diamantoulakis, A. Liopa-Tsakalidi, P. Barouchas, G. Salahas, G. Karagiannidis, S. Wan, and S. K. Goudos, "Internet of Things (IoT) and Agricultural Unmanned Aerial Vehicles (UAVs) in smart farming: A comprehensive review," *Internet of Things*, no. xxxx, p. 100187, 2020. [Online]. Available: https://doi.org/10.1016/j.iot.2020.100187

[21] K. Jha, A. Doshi, P. Patel, and M. Shah, "A comprehensive review on automation in agriculture using artificial intelligence," *Artificial Intelligence in Agriculture*, vol. 2, pp. 1–12, 2019. [Online]. Available: https://doi.org/10.1016/j.aiia.2019.05.004

[22] O. Elijah, T. A. Rahman, I. Orikumhi, C. Y. Leow, and M. N. Hindia, "An Overview of Internet of Things (IoT) and Data Analytics in Agriculture: Benefits and Challenges," *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 3758–3773, 2018.

[23] M. Mohammadi, A. Al-Fuqaha, S. Sorour, and M. Guizani, "Deep learning for IoT big data and streaming analytics: A survey," *arXiv*, vol. 20, no. 4, pp. 2923–2960, 2017.

[24] M. Kulbacki, J. Segen, W. Knieć, R. Klempous, K. Kluwak, J. Nikodem, J. Kulbacka, and A. Serester, "Survey of Drones for Agriculture Automation from Planting to Harvest," *INES 2018 - IEEE 22nd International Conference on Intelligent Engineering Systems, Proceedings*, pp. 000 353–000 358, 2018.

[25] M. S. Ali, M. Vecchio, M. Pincheira, K. Dolui, F. Antonelli, and M. H. Rehmani, "Applications of Blockchains in the Internet of Things: A Comprehensive Survey," *IEEE Communications Surveys and Tutorials*, vol. 21, no. 2, pp. 1676–1717, 2019.

[26] M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour, and E. H. M. Aggoune, "Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk," *IEEE Access*, vol. 7, pp. 129 551–129 583, 2019.

[27] M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, "A Survey on the Role of IoT in Agriculture for the Implementation of Smart Farming," *IEEE Access*, vol. 7, pp. 156 237–156 271, 2019.

[28] V. P. Kour and S. Arora, "Recent Developments of the Internet of Things in Agriculture: A Survey," *IEEE Access*, vol. 8, pp. 129 924–129 957, 2020.

[29] M. S. Farooq, S. Riaz, A. Abid, T. Umer, and Y. B. Zikria, "Role of iot technology in agriculture: A systematic literature review," *Electronics (Switzerland)*, vol. 9, no. 2, 2020.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

[30] U. Bodkhe, S. Tanwar, P. Bhattacharya, and N. Kumar, "Blockchain for precision irrigation: Opportunities and challenges," *Transactions on Emerging Telecommunications Technologies*, no. March, pp. 1–30, 2020.

[31] D. C. Tsouros, S. Bibi, and P. G. Sarigiannidis, "A review on UAV-based applications for precision agriculture," *Information (Switzerland)*, vol. 10, no. 11, 2019.

[32] Y. Mekonnen, S. Namuduri, L. Burton, A. Sarwat, and S. Bhansali, "Review—Machine Learning Techniques in Wireless Sensor Network Based Precision Agriculture," *Journal of The Electrochemical Society*, vol. 167, no. 3, p. 037522, 2020.

[33] R. P. Sishodia, R. L. Ray, and S. K. Singh, "Applications of remote sensing in precision agriculture: A review," *Remote Sensing*, vol. 12, no. 19, pp. 1–31, 2020.

[34] F. J. Ferrández-Pastor, J. M. García-Chamizo, M. Nieto-Hidalgo, and J. Mora-Martínez, "Precision agriculture design method using a distributed computing architecture on internet of things context," *Sensors (Switzerland)*, vol. 18, no. 6, 2018.

[35] U. Shafi, R. Mumtaz, J. García-Nieto, S. A. Hassan, S. A. R. Zaidi, and N. Iqbal, "Precision agriculture techniques and practices: From considerations to applications," *Sensors (Switzerland)*, vol. 19, no. 17, pp. 1–25, 2019.

[36] D. Thakur, Y. Kumar, A. Kumar, and P. K. Singh, *Applicability of Wireless Sensor Networks in Precision Agriculture: A Review*. Springer US, 2019, vol. 107, no. 1. [Online]. Available: https://doi.org/10.1007/s11277-019-06285-2

[37] G. Vitali, M. Francia, M. Golfarelli, and M. Canavari, "Crop management with the iot: An interdisciplinary survey," *Agronomy*, vol. 11, no. 1, 2021. [Online]. Available: https://www.mdpi.com/2073-4395/11/1/181

[38] M. A. Ferrag, L. Shu, X. Yang, A. Derhab, and L. Maglaras, "Security and Privacy for Green IoT-Based Agriculture: Review, Blockchain Solutions, and Challenges," *IEEE Access*, vol. 8, pp. 32 031–32 053, 2020.

[39] IEEE, "Ieee standards activities in the internet of things (iot)," IEEE Standards, Tech. Rep.

[40] F. Zulfiqar, M. Navarro, M. Ashraf, N. A. Akram, and S. Munné-Bosch, "Nanofertilizer use for sustainable agriculture: Advantages and limitations," *Plant Science*, vol. 289, no. August, 2019.

[41] J. S. Duhan, R. Kumar, N. Kumar, P. Kaur, K. Nehra, and S. Duhan, "Nanotechnology: The new perspective in precision agriculture," *Biotechnology Reports*, vol. 15, no. December 2016, pp. 11–23, 2017.

[42] N. Dasgupta, S. Ranjan, and C. Ramalingam, "Applications of nanotechnology in agriculture and water quality management," *Environmental Chemistry Letters*, vol. 15, no. 4, pp. 591–605, 2017.

[43] H. Chhipa, "Nanofertilizers and nanopesticides for agriculture," *Environmental Chemistry Letters*, vol. 15, no. 1, pp. 15–22, 2017.

[44] A. K. Srivastava, A. Dev, and S. Karmakar, "Nanosensors and nanobiosensors in food and agriculture," *Environmental Chemistry Letters*, vol. 16, no. 1, pp. 161–182, 2018. [Online]. Available: https://doi.org/10.1007/s10311-017-0674-7

[45] X. He, H. Deng, and H. min Hwang, "The current application of nanotechnology in food and agriculture," *Journal of Food and Drug Analysis*, vol. 27, no. 1, pp. 1–21, 2019. [Online]. Available: https://doi.org/10.1016/j.jfda.2018.12.002

[46] R. Prasad, A. Bhattacharyya, and Q. D. Nguyen, "Nanotechnology in sustainable agriculture: Recent developments, challenges, and perspectives," *Frontiers in Microbiology*, vol. 8, no. JUN, pp. 1–13, 2017.

[47] I. Iavicoli, V. Leso, D. H. Beezhold, and A. A. Shvedova, "Nanotechnology in agriculture: Opportunities, toxicological implications, and occupational risks," *Toxicology and Applied Pharmacology*, vol. 329, pp. 96–111, 2017. [Online]. Available: http://dx.doi.org/10.1016/j.taap.2017.05.025

[48] R. Raliya, V. Saharan, C. Dimkpa, and P. Biswas, "Nanofertilizer for Precision and Sustainable Agriculture: Current State and Future Perspectives," *Journal of Agricultural and Food Chemistry*, vol. 66, no. 26, pp. 6487–6503, 2018.

[49] R. K. Singh, M. Aernouts, M. De Meyer, M. Weyn, and R. Berkvens, "Leveraging LoRaWAN technology for precision agriculture in greenhouses," *Sensors (Switzerland)*, vol. 20, no. 7, 2020.

[50] K. Lova Raju and V. Vijayaraghavan, *IoT Technologies in Agricultural Environment: A Survey*. Springer US, 2020, vol. 113, no. 4. [Online]. Available: https://doi.org/10.1007/s11277-020-07334-x

[51] A. Zervopoulos, A. Tsipis, A. G. Alvanou, K. Bezas, A. Papamichail, S. Vergis, A. Stylidou, G. Tsoumanis, V. Komianos, G. Koufoudakis, and K. Oikonomou, "Wireless sensor network synchronization for precision agriculture applications," *Agriculture (Switzerland)*, vol. 10, no. 3, pp. 1–20, 2020.

[52] T. Wang, S. C. Liew, and S. Zhang, "When blockchain meets AI: Optimal mining strategy achieved by machine learning," *arXiv*, vol. 1, no. 1, pp. 1–18, 2019.

[53] A. D. Boursianis, M. S. Papadopoulou, A. Gotsis, S. Wan, P. Sarigiannidis, S. Nikolaidis, and S. K. Goudos, "Smart Irrigation System for Precision Agriculture - The AREThOU5A IoT Platform," *IEEE Sensors Journal*, vol. XX, no. XX, pp. 1–1, 2020.

[54] H. Agrawal, R. Dhall, K. S. Iyer, and V. Chetlapalli, "An improved energy efficient system for IoT enabled precision agriculture," *Journal of Ambient Intelligence and Humanized Computing*, vol. 11, no. 6, pp. 2337–2348, 2020. [Online]. Available: https://doi.org/10.1007/s12652-019-01359-2

[55] A. H. Mohd Aman, E. Yadegaridehkordi, Z. S. Attarbashi, R. Hassan, and Y. J. Park, "A Survey on Trend and Classification of Internet of Things Reviews," *IEEE Access*, vol. 8, pp. 111 763–111 782, 2020.

[56] M. A. Al-Garadi, A. Mohamed, A. Al-Ali, X. Du, and M. Guizani, "A survey of machine and deep learning methods for internet of things (IoT) security," *arXiv*, vol. 22, no. 3, pp. 1646–1685, 2018.

[57] X. Shi, X. An, Q. Zhao, H. Liu, L. Xia, X. Sun, and Y. Guo, "State-of-the-art internet of things in protected agriculture," *Sensors (Switzerland)*, vol. 19, no. 8, 2019.

[58] A. Triantafyllou, P. Sarigiannidis, and S. Bibi, "Precision agriculture: A remote sensing monitoring system architecture," *Information (Switzerland)*, vol. 10, no. 11, 2019.

[59] L. García, L. Parra, J. M. Jimenez, J. Lloret, and P. Lorenz, "IoT-based smart irrigation systems: An overview on the recent trends on sensors and iot systems for irrigation in precision agriculture," *Sensors (Switzerland)*, vol. 20, no. 4, 2020.

[60] C. Yoon, M. Huh, S. G. Kang, J. Park, and C. Lee, "Implement smart farm with IoT technology," *International Conference on Advanced Communication Technology, ICACT*, vol. 2018-Febru, pp. 749–752, 2018.

[61] A. L. P. De Ocampo and E. P. Dadios, "Energy cost optimization in irrigation system of smart farm by using genetic algorithm," *HNICEM 2017 - 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management*, vol. 2018-January, pp. 1–7, 2017.

[62] H. L. Shi, K. M. Hou, X. Diao, L. Xing, J. J. Li, and C. De Vaulx, "A wireless multimedia sensor network platform for environmental event detection dedicated to precision agriculture," *arXiv*, 2018.

[63] C. Kamienski, J. P. Soininen, M. Taumberger, R. Dantas, A. Toscano, T. S. Cinotti, R. F. Maia, and A. T. Neto, "Smart water management platform: IoT-based precision irrigation for agriculture," *Sensors (Switzerland)*, vol. 19, no. 2, 2019.

[64] V. Palazzi, F. Gelati, U. Vaglioni, F. Alimenti, P. Mezzanotte, and L. Roselli, "Leaf-Compatible Autonomous RFID-Based Wireless Temperature Sensors for Precision Agriculture," *2019 IEEE Topical Conference on Wireless Sensors and Sensor Networks, WiSNet 2019*, pp. 2019–2022, 2019.

[65] Y. Tian, B. Zheng, and Z. Li, "Agricultural greenhouse environment monitoring system based on Internet of Things," *2017 3rd IEEE International Conference on Computer and Communications, ICCC 2017*, vol. 2018-Janua, pp. 2981–2985, 2018.

[66] A. A. A. Halim, N. M. Hassan, A. Zakaria, L. M. Kamarudin, and A. H. A. Bakar, "Internet of things technology for greenhouse monitoring and management system based on wireless sensor network," *ARPN Journal of Engineering and Applied Sciences*, vol. 11, no. 22, pp. 13 169–13 175, 2016.

[67] O. Adeyemi, I. Grove, S. Peets, and T. Norton, "Advanced monitoring and management systems for improving sustainability in precision irrigation," *Sustainability (Switzerland)*, vol. 9, no. 3, pp. 1–29, 2017.

[68] T. A. Khoa, M. M. Man, T. Y. Nguyen, V. D. Nguyen, and N. H. Nam, "Smart agriculture using IoT multi-sensors: A novel watering management system," *Journal of Sensor and Actuator Networks*, vol. 8, no. 3, 2019.

[69] G. S. Nagaraja, A. B. Soppimath, T. Soumya, and A. Abhinith, "IoT Based Smart Agriculture Management System," *CSITSS 2019 - 2019 4th International Conference on Computational Systems and Information Technology for Sustainable Solution, Proceedings*, 2019.

[70] M. S. Croock, S. Al-Qaraawi, and Q. S. Hamad, "Efficient wireless sensor network based monitoring system," *Ad-Hoc and Sensor Wireless Networks*, vol. 35, no. 1-2, pp. 105–128, 2017.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

[71] K. Foughali, K. Fathallah, and A. Frihida, "Using Cloud IOT for disease prevention in precision agriculture," *Procedia Computer Science*, vol. 130, pp. 575–582, 2018. [Online]. Available: https://doi.org/10.1016/j.procs.2018.04.106

[72] E. Guardo, A. Di Stefano, A. L. Corte, M. Sapienza, and M. Scatà, "A fog computing-based IoT framework for precision agriculture," *Journal of Internet Technology*, vol. 19, no. 5, pp. 1401–1411, 2018.

[73] K. P. Ferentinos, N. Katsoulas, A. Tzounis, T. Bartzanas, and C. Kittas, "Wireless sensor networks for greenhouse climate and plant condition assessment," *Biosystems Engineering*, vol. 153, pp. 70–81, 2017. [Online]. Available: http://dx.doi.org/10.1016/j.biosystemseng.2016.11.005

[74] S. Rodríguez, T. Gualotuña, and C. Grilo, "A System for the Monitoring and Predicting of Data in Precision Agriculture in a Rose Greenhouse Based on Wireless Sensor Networks," *Procedia Computer Science*, vol. 121, pp. 306–313, 2017. [Online]. Available: https://doi.org/10.1016/j.procs.2017.11.042

[75] H. S. Abdullahi, R. E. Sheriff, and F. Mahieddine, "Convolution neural network in precision agriculture for plant image recognition and classification," no. August, pp. 1–3, 2017.

[76] M. Fawakherji, A. Youssef, D. Bloisi, A. Pretto, and D. Nardi, "Crop and Weeds Classification for Precision Agriculture Using Context-Independent Pixel-Wise Segmentation," *Proceedings - 3rd IEEE International Conference on Robotic Computing, IRC 2019*, pp. 146–152, 2019.

[77] V. Mazzia, L. Comba, A. Khaliq, M. Chiaberge, and P. Gay, "UAV and Machine Learning Based Refinement of a Satellite-Driven Vegetation Index for Precision Agriculture †," *arXiv*, 2020.

[78] M. T. Chiu, X. Xu, Y. Wei, Z. Huang, A. Schwing, R. Brunner, H. Khachatrian, H. Karapetyan, I. Dozier, G. Rose, D. Wilson, A. Tudor, N. Hovakimyan, T. S. Huang, and H. Shi, "Agriculture-Vision: A Large Aerial Image Database for Agricultural Pattern Analysis," *arXiv*, pp. 2828–2838, 2020.

[79] U. J. L. dos Santos, G. Pessin, C. A. da Costa, and R. da Rosa Righi, "AgriPrediction: A proactive internet of things model to anticipate problems and improve production in agricultural crops," *Computers and Electronics in Agriculture*, vol. 161, no. November 2017, pp. 202–213, 2019. [Online]. Available: https://doi.org/10.1016/j.compag.2018.10.010

[80] X. Pham and M. Stack, "How data analytics is transforming agriculture," *Business Horizons*, vol. 61, no. 1, pp. 125–133, 2018. [Online]. Available: http://dx.doi.org/10.1016/j.bushor.2017.09.011

[81] D. I. Patrício and R. Rieder, "Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review," *Computers and Electronics in Agriculture*, vol. 153, no. August, pp. 69–81, 2018.

[82] B. Lu, P. D. Dao, J. Liu, Y. He, and J. Shang, "Recent advances of hyperspectral imaging technology and applications in agriculture," *Remote Sensing*, vol. 12, no. 16, pp. 1–44, 2020.

[83] P. Bosilj, T. Duckett, and G. Cielniak, "Analysis of Morphology-Based Features for Classification of Crop and Weeds in Precision Agriculture," *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 2950–2956, 2018.

[84] P. Toscano, A. Castrignanò, S. F. Di Gennaro, A. V. Vonella, D. Ventrella, and A. Matese, "A precision agriculture approach for durum wheat yield assessment using remote sensing data and yield mapping," *Agronomy*, vol. 9, no. 8, 2019.

[85] S. Ahirwar, R. Swarnkar, S. Bhukya, and G. Namwade, "Application of Drone in Agriculture," *International Journal of Current Microbiology and Applied Sciences*, vol. 8, no. 01, pp. 2500–2505, 2019.

[86] V. Marinoudi, C. G. Sørensen, S. Pearson, and D. Bochtis, "Robotics and labour in agriculture. A context consideration," *Biosystems Engineering*, vol. 184, pp. 111–121, 2019. [Online]. Available: https://doi.org/10.1016/j.biosystemseng.2019.06.013

[87] A. Selmani, H. Oubehar, M. Outanoute, A. Ed-Dahhak, M. Guerbaoui, A. Lachhab, and B. Bouchikhi, "Agricultural cyber-physical system enabled for remote management of solar-powered precision irrigation," *Biosystems Engineering*, vol. 177, pp. 18–30, 2019. [Online]. Available: https://doi.org/10.1016/j.biosystemseng.2018.06.007

[88] M. Gupta, M. Abdelsalam, S. Khorsandroo, and S. Mittal, "Security and Privacy in Smart Farming: Challenges and Opportunities," *IEEE Access*, vol. 8, pp. 34 564–34 584, 2020.

[89] Y.-P. Lin, J. Petway, J. Anthony, H. Mukhtar, S.-W. Liao, C.-F. Chou, and Y.-F. Ho, "Blockchain: The Evolutionary Next Step for ICT E-Agriculture," *Environments*, vol. 4, no. 3, p. 50, 2017.

[90] S. Green, "Decentralized Agriculture: Applying Blockchain Technology in Agri-Food Markets," 2018.

[91] T. Alladi, V. Chamola, J. J. Rodrigues, and S. A. Kozlov, "Blockchain in smart grids: A review on different use cases," *Sensors (Switzerland)*, vol. 19, no. 22, pp. 1–25, 2019.

[92] J. Lin, A. Zhang, Z. Shen, and Y. Chai, "Blockchain and IoT based food traceability for smart agriculture," *ACM International Conference Proceeding Series*, pp. 1–6, 2018.

[93] T. Nguyen, J. P. Queralta, T. Nguyen Gia, L. Qingqing, J. Peña Queralta, Z. Zou, H. Tenhunen, and T. Westerlund, "Edge AI in Smart Farming IoT: CNNs at the Edge and Fog Computing with LoRa Education Technology View project Design Methodology for On-Chip Multi-core Embedded Systems (DOMES) View project Edge AI in Smart Farming IoT: CNNs at the Edge and Fog Computing w," no. September, 2019. [Online]. Available: https://www.researchgate.net/publication/335062264

[94] J. Lu, L. Feng, J. Yang, M. M. Hassan, A. Alelaiwi, and I. Humar, "Artificial agent: The fusion of artificial intelligence and a mobile agent for energy-efficient traffic control in wireless sensor networks," *Future Generation Computer Systems*, vol. 95, pp. 45–51, 2019. [Online]. Available: https://doi.org/10.1016/j.future.2018.12.024

[95] A. Nabavi-Pelesaraei, S. Rafiee, S. S. Mohtasebi, H. Hosseinzadeh-Bandbafha, and K. wing Chau, "Integration of artificial intelligence methods and life cycle assessment to predict energy output and environmental impacts of paddy production," *Science of the Total Environment*, vol. 631-632, pp. 1279–1294, 2018.

[96] S. Chaterji, N. DeLay, J. Evans, N. Mosier, B. Engel, D. Buckmaster, and R. Chandra, "Artificial Intelligence for Digital Agriculture at Scale: Techniques, Policies, and Challenges," pp. 1–15, 2020. [Online]. Available: http://arxiv.org/abs/2001.09786

[97] D. I. Patrício and R. Rieder, "Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review," *Computers and Electronics in Agriculture*, vol. 153, no. June, pp. 69–81, 2018.

[98] D. Shadrin, A. Menshchikov, A. Somov, G. Bornemann, J. Hauslage, and M. Fedorov, "Enabling Precision Agriculture through Embedded Sensing with Artificial Intelligence," *IEEE Transactions on Instrumentation and Measurement*, vol. 9456, no. c, pp. 1–1, 2019.

[99] D. Alfer'ev, "Artificial intelligence in agriculture," *Agricultural and Lifestock Technology /* , vol. 7, no. 4 (4), 2018.

[100] S. Hemming, F. De Zwart, A. Elings, I. Righini, and A. Petropoulou, "Remote control of greenhouse vegetable production with artificial intelligence—greenhouse climate, irrigation, and crop production," *Sensors (Switzerland)*, vol. 19, no. 8, 2019.

[101] D. Alfer'ev, "Artificial intelligence in agriculture," *Agricultural and Lifestock Technology /* , no. 4 (4), 2018.

[102] V. Lakshmi and J. Corbett, "How Artificial Intelligence Improves Agricultural Productivity and Sustainability: A Global Thematic Analysis," *Proceedings of the 53rd Hawaii International Conference on System Sciences*, vol. 3, pp. 5202–5211, 2020.

[103] A. Khattab, A. Abdelgawad, and K. Yelmarthi, "Design and implementation of a cloud-based IoT scheme for precision agriculture," *Proceedings of the International Conference on Microelectronics, ICM*, vol. 0, pp. 201–204, 2016.

[104] R. Morais, N. Silva, J. Mendes, T. Adão, L. Pádua, J. A. López-Riquelme, N. Pavón-Pulido, J. J. Sousa, and E. Peres, "mySense: A comprehensive data management environment to improve precision agriculture practices," *Computers and Electronics in Agriculture*, vol. 162, no. March, pp. 882–894, 2019. [Online]. Available: https://doi.org/10.1016/j.compag.2019.05.028

[105] F. Karim, F. Karim, and A. Frihida, "Monitoring system using web of things in precision agriculture," *Procedia Computer Science*, vol. 110, pp. 402–409, 2017. [Online]. Available: http://dx.doi.org/10.1016/j.procs.2017.06.083

[106] M. A. Zamora-Izquierdo, J. Santa, J. A. Martínez, V. Martínez, and A. F. Skarmeta, "Smart farming IoT platform based on edge and cloud computing," *Biosystems Engineering*, vol. 177, pp. 4–17, 2019.

[107] S. Vatari, A. Bakshi, and T. Thakur, "Green house by using IOT and cloud computing," *2016 IEEE International Conference on Recent Trends in Electronics, Information and Communication Technology, RTEICT 2016 - Proceedings*, pp. 246–250, 2017.

[108] E. Symeonaki, K. Arvanitis, and D. Piromalis, "A context-aware middleware cloud approach for integrating precision farming facilities into the IoT toward agriculture 4.0," *Applied Sciences (Switzerland)*, vol. 10, no. 3, 2020.

[109] R. R. Shamshiri, F. Kalantari, K. C. Ting, K. R. Thorp, I. A. Hameed, C. Weltzien, D. Ahmad, and Z. Shad, "Advances in greenhouse automation and controlled environment agriculture: A transition to plant

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

factories and urban agriculture," *International Journal of Agricultural and Biological Engineering*, vol. 11, no. 1, pp. 1–22, 2018.

[110] J. Muangprathub, N. Boonnam, S. Kajornkasirat, N. Lekbangpong, A. Wanichsombat, and P. Nillaor, "IoT and agriculture data analysis for smart farm," *Computers and Electronics in Agriculture*, vol. 156, no. June 2018, pp. 467–474, 2019. [Online]. Available: https://doi.org/10.1016/j.compag.2018.12.011

[111] G. Aiello, I. Giovino, M. Vallone, P. Catania, and A. Argento, "A decision support system based on multisensor data fusion for sustainable greenhouse management," *Journal of Cleaner Production*, vol. 172, pp. 4057–4065, 2018. [Online]. Available: https://doi.org/10.1016/j.jclepro.2017.02.197

[112] R. Dhall and H. Agrawal, "An improved energy efficient duty cycling algorithm for IoT based precision agriculture," *Procedia Computer Science*, vol. 141, pp. 135–142, 2018. [Online]. Available: https://doi.org/10.1016/j.procs.2018.10.159

[113] M. Saqib, T. A. Almohamad, and R. M. Mehmood, "A low-cost information monitoring system for smart farming applications," *Sensors (Switzerland)*, vol. 20, no. 8, 2020.

[114] T. Aishwarya Lakshmi, B. Hariharan, and P. Rekha, "A Survey on Energy Efficient Routing Protocol for IoT Based Precision Agriculture," *Proceedings of the 4th International Conference on Communication and Electronics Systems, ICCES 2019*, no. Icces, pp. 1284–1288, 2019.

[115] C. Yang, S. Yuling, W. Zhongyi, and H. Lan, "Connectivity of wireless sensor networks in greenhouse for plant growth," *International Journal of Agricultural and Biological Engineering*, vol. 9, no. 1, pp. 89–98–98, 2016.

[116] S. Saraswat, A. Tripathi, H. P. Gupta, and T. Dutta, "An Energy Efficient Monitoring System for Precision Agriculture in Wireless Sensor Networks," pp. 46–49, 2018.

[117] S. Maurya and V. K. Jain, "Energy-Efficient Network Protocol for Precision Agriculture: Using threshold sensitive sensors for optimal performance," *IEEE Consumer Electronics Magazine*, vol. 6, no. 3, pp. 42–51, 2017.

[118] H. M. Jawad, R. Nordin, S. K. Gharghan, A. M. Jawad, M. Ismail, and M. J. Abu-Alshaeer, "Power reduction with sleep/wake on redundant data (SWORD) in a wireless sensor network for energy-efficient precision agriculture," *Sensors (Switzerland)*, vol. 18, no. 10, 2018.

[119] H. M. Jawad, R. Nordin, S. K. Gharghan, A. M. Jawad, and M. Ismail, "Energy-efficient wireless sensor networks for precision agriculture: A review," 2017.

[120] Y. Hamouda and M. Msallam, "Variable sampling interval for energy-efficient heterogeneous precision agriculture using Wireless Sensor Networks," *Journal of King Saud University - Computer and Information Sciences*, vol. 32, no. 1, pp. 88–98, 2020. [Online]. Available: https://doi.org/10.1016/j.jksuci.2018.04.010

[121] M. Srbinovska, V. Dimcev, and C. Gavrovski, "Energy consumption estimation of wireless sensor networks in greenhouse crop production," *17th IEEE International Conference on Smart Technologies, EUROCON 2017 - Conference Proceedings*, no. July, pp. 870–875, 2017.

[122] C. Yang, S. Yuling, W. Zhongyi, and H. Lan, "Connectivity of wireless sensor networks in greenhouse for plant growth," *International Journal of Agricultural and Biological Engineering*, vol. 9, no. 1, pp. 89–98–98, 2016.

[123] C. Del-Valle-Soto, L. J. Valdivia, R. Velázquez, L. Rizo-Dominguez, and J. C. López-Pimentel, "Smart campus: An experimental performance comparison of collaborative and cooperative schemes for wireless sensor network," *Energies*, vol. 12, no. 16, 2019.

[124] S. Wu, K. I. Wang, A. Ivoghlian, Z. Salcic, A. Austin, and X. Zhou, "LWS: A LoRaWAN wireless underground sensor network simulator for agriculture applications," *Proceedings - 2019 IEEE SmartWorld, Ubiquitous Intelligence and Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Internet of People and Smart City Innovation, SmartWorld/UIC/ATC/SCALCOM/IOP/SCI 2019*, pp. 475–482, 2019.

[125] B. M. Njoroge, T. K. Fei, and V. Thiruchelvam, "A research review of precision farming techniques and technology," *Journal of Applied Technology and Innovation*, vol. 2, no. 1, pp. 22–30, 2018. [Online]. Available: https://jati.sites.apiit.edu.my/files/2018/07/2018{_}Issue1{_}Paper4.pdf

[126] M. Bacco, P. Barsocchi, E. Ferro, A. Gotta, and M. Ruggeri, "The Digitisation of Agriculture: a Survey of Research Activities on Smart Farming," *Array*, vol. 3-4, no. October, p. 100009, 2019. [Online]. Available: https://doi.org/10.1016/j.array.2019.100009

[127] S. Y. Chang, P. Cheng, G. Li, and Y. Yang, "Transparent Polymer Photovoltaics for Solar Energy Harvesting and Beyond," *Joule*, vol. 2, no. 6, pp. 1039–1054, 2018. [Online]. Available: https://doi.org/10.1016/j.joule.2018.04.005

[128] S. Sadowski and P. Spachos, "Solar-Powered Smart Agricultural Monitoring System Using Internet of Things Devices," *2018 IEEE 9th Annual Information Technology, Electronics and Mobile Communication Conference, IEMCON 2018*, pp. 18–23, 2019.

[129] H. H. R. Sherazi, L. A. Grieco, and G. Boggia, "A comprehensive review on energy harvesting MAC protocols in WSNs: Challenges and tradeoffs," *Ad Hoc Networks*, vol. 71, pp. 117–134, 2018. [Online]. Available: https://doi.org/10.1016/j.adhoc.2018.01.004

[130] P.-D. Gleonec, "Design and implementation of power management strategies for long range radio modules with energy harvesting," Theses, Université de Rennes 1 [UR1], Feb. 2019. [Online]. Available: https://tel.archives-ouvertes.fr/tel-02131685

[131] L. Sigrist, N. Stricker, D. Bernath, J. Beutel, and L. Thiele, "Thermoelectric Energy Harvesting from Gradients in the Earth Surface," *IEEE Transactions on Industrial Electronics*, vol. PP, no. c, p. 1, 2019.

[132] B. Omoniwa, R. Hussain, M. A. Javed, S. H. Bouk, S. Member, and S. A. Malik, "Fog / Edge Computing-Based IoT (FECIoT):," vol. 6, no. 3, pp. 4118–4149, 2019.

[133] M. O'Grady, D. Langton, and G. O'Hare, "Edge computing: A tractable model for smart agriculture?" *Artificial Intelligence in Agriculture*, vol. 3, pp. 42–51, 2019. [Online]. Available: https://doi.org/10.1016/j.aiia.2019.12.001

[134] C. Perera, Y. Qin, J. C. Estrella, S. Reiff-Marganiec, and A. V. Vasilakos, "Fog computing for sustainable smart cities: A survey," *ACM Computing Surveys*, vol. 50, no. 3, 2017.

[135] V. K. Sarker, J. P. Queralta, T. N. Gia, H. Tenhunen, and T. Westerlund, "A survey on LoRa for IoT: Integrating edge computing," *2019 4th International Conference on Fog and Mobile Edge Computing, FMEC 2019*, pp. 295–300, 2019.

[136] D. Taşkın, C. Taşkın, and S. Yazar, "Developing a Bluetooth Low Energy Sensor Node for Greenhouse in Precision Agriculture as Internet of Things Application," *Advances in Science and Technology Research Journal*, vol. 12, no. 4, pp. 88–96, 2018.

[137] F. J. Ferrández-Pastor, J. M. García-Chamizo, M. Nieto-Hidalgo, J. Mora-Pascual, and J. Mora-Martínez, "Developing ubiquitous sensor network platform using internet of things: Application in precision agriculture," *Sensors (Switzerland)*, vol. 16, no. 7, 2016.

[138] P. P. Ray, "A survey on Internet of Things architectures," *Journal of King Saud University - Computer and Information Sciences*, vol. 30, no. 3, pp. 291–319, 2018. [Online]. Available: https://doi.org/10.1016/j.jksuci.2016.10.003

[139] R. C. Andrew, R. Malekian, and D. C. Bogatinoska, "IoT solutions for precision agriculture," *2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics, MIPRO 2018 - Proceedings*, pp. 345–349, 2018.

[140] M. Ndiaye, G. P. Hancke, and A. M. Abu-Mahfouz, "Software defined networking for improved wireless sensor network management: A survey," *Sensors (Switzerland)*, vol. 17, no. 5, pp. 1–32, 2017.

[141] K. Mahmud, B. Khan, J. Ravishankar, A. Ahmadi, and P. Siano, "An internet of energy framework with distributed energy resources, prosumers and small-scale virtual power plants: An overview," *Renewable and Sustainable Energy Reviews*, vol. 127, no. June 2019, p. 109840, 2020. [Online]. Available: https://doi.org/10.1016/j.rser.2020.109840

[142] W. Xue-Fen, Y. Yi, Z. Tao, Z. Jing-Wen, and M. S. Sardar, "Design of distributed agricultural service node with smartphone in-field access supporting for smart farming in Beijing-Tianjin-Hebei region," *Sensors and Materials*, vol. 30, no. 10, pp. 2281–2293, 2018.

[143] Köksal and B. Tekinerdogan, "Architecture design approach for IoT-based farm management information systems," *Precision Agriculture*, vol. 20, no. 5, pp. 926–958, 2019. [Online]. Available: https://doi.org/10.1007/s11119-018-09624-8

[144] G. Codeluppi, A. Cilfone, L. Davoli, and G. Ferrari, "LoraFarM: A LoRaWAN-based smart farming modular IoT architecture," *Sensors (Switzerland)*, vol. 20, no. 7, 2020.

[145] P. P. Peerapak Lerdsuwan, "An Energy-Efficient Transmission Framework for IoT Monitoring Systems in Precision Agriculture." Singapore: Springer Singapore, 2017, pp. 714—-721. [Online]. Available: https://link.springer.com/chapter/10.1007/978-981-10-4154-9{_}82

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

[146] L. Nóbrega, P. Gonçalves, P. Pedreiras, and J. Pereira, "An IoT-based solution for intelligent farming," *Sensors (Switzerland)*, vol. 19, no. 3, pp. 1–24, 2019.

[147] A. Salam, A. D. Hoang, A. Meghna, D. R. Martin, G. A. Guzman, Y. H. Yoon, J. B. Carlson, J. L. Kramer, K. Yansi, M. G. Kelly, M. J. Skvarek, M. Stankovic, N. Dang, K. Le, and T. A. Wierzbicki, "The Future of Emerging IoT Paradigms : Architectures and Technologies," no. December, 2019.

[148] A. Lytos, T. Lagkas, P. Sarigiannidis, M. Zervakis, and G. Livanos, "Towards smart farming: Systems, frameworks and exploitation of multiple sources," *Computer Networks*, vol. 172, no. January, p. 107147, 2020. [Online]. Available: https://doi.org/10.1016/j.comnet.2020.107147

[149] Y. Song, J. Lin, M. Tang, and S. Dong, "An Internet of Energy Things Based on Wireless LPWAN," *Engineering*, vol. 3, no. 4, pp. 460–466, 2017. [Online]. Available: http://dx.doi.org/10.1016/J.ENG.2017.04.011

[150] M. Chen, Y. Miao, X. Jian, X. Wang, and I. Humar, "Cognitive-LPWAN: Towards Intelligent Wireless Services in Hybrid Low Power Wide Area Networks," *IEEE Transactions on Green Communications and Networking*, vol. 3, no. 2, pp. 409–417, 2019.

[151] K. Mekki, E. Bajic, F. Chaxel, and F. Meyer, "A comparative study of LPWAN technologies for large-scale IoT deployment," *ICT Express*, vol. 5, no. 1, pp. 1–7, 2019. [Online]. Available: https://doi.org/10.1016/j.icte.2017.12.005

[152] R. K. Singh, P. P. Puluckul, R. Berkvens, and M. Weyn, "Energy consumption analysis of lpwan technologies and lifetime estimation for iot application," *Sensors*, vol. 20, no. 17, 2020. [Online]. Available: https://www.mdpi.com/1424-8220/20/17/4794

[153] T. Anh Khoa, C. H. Phuc, P. D. Lam, L. M. B. Nhu, N. M. Trong, N. T. H. Phuong, N. V. Dung, N. Tan-Y, H. N. Nguyen, and D. N. M. Duc, "Waste Management System Using IoT-Based Machine Learning in University," *Wireless Communications and Mobile Computing*, vol. 2020, pp. 1–13, 2020.

[154] D. Brunelli, A. Albanese, D. Acunto, and M. Nardello, "E nergy N eutral M achine L earning B ased I o T D evice for P est D etection in P recision A griculture," no. December 2019, pp. 10–13, 2020.

[155] S. Dimitriadis and C. Goumopoulos, "Applying machine learning to extract new knowledge in precision agriculture applications," *Proceedings - 12th Pan-Hellenic Conference on Informatics, PCI 2008*, pp. 100–104, 2008.

[156] A. Chlingaryan, S. Sukkarieh, and B. Whelan, "Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review," *Computers and Electronics in Agriculture*, vol. 151, no. November 2017, pp. 61–69, 2018. [Online]. Available: https://doi.org/10.1016/j.compag.2018.05.012

[157] K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine learning in agriculture: A review," *Sensors (Switzerland)*, vol. 18, no. 8, pp. 1–29, 2018.

[158] Y. Y. Zheng, J. L. Kong, X. B. Jin, X. Y. Wang, T. L. Su, and M. Zuo, "Cropdeep: The crop vision dataset for deep-learning-based classification and detection in precision agriculture," *Sensors (Switzerland)*, vol. 19, no. 5, 2019.

[159] A. Chlingaryan, S. Sukkarieh, and B. Whelan, "Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review," *Computers and Electronics in Agriculture*, vol. 151, no. June, pp. 61–69, 2018. [Online]. Available: https://doi.org/10.1016/j.compag.2018.05.012

[160] R. B. Sorensen, J. J. Nielsen, and P. Popovski, "Machine Learning Methods for Monitoring of Quasi-Periodic Traffic in Massive IoT Networks," *IEEE Internet of Things Journal*, vol. 4662, no. c, pp. 1–1, 2020.

[161] S. Dimitriadis and C. Goumopoulos, "Applying machine learning to extract new knowledge in precision agriculture applications," *Proceedings - 12th Pan-Hellenic Conference on Informatics, PCI 2008*, pp. 100–104, 2008.

[162] Y. Vecchio, M. De Rosa, F. Adinolfi, L. Bartoli, and M. Masi, "Adoption of precision farming tools: A context-related analysis," *Land Use Policy*, vol. 94, no. July 2019, p. 104481, 2020. [Online]. Available: https://doi.org/10.1016/j.landusepol.2020.104481

[163] Y. Ampatzidis, L. D. Bellis, and A. Luvisi, "iPathology: Robotic applications and management of plants and plant diseases," *Sustainability (Switzerland)*, vol. 9, no. 6, pp. 1–14, 2017.

[164] N. Pavón-Pulido, J. A. López-Riquelme, R. Torres, R. Morais, and J. A. Pastor, "New trends in precision agriculture: a novel cloud-based system for enabling data storage and agricultural task planning and automation," *Precision Agriculture*, vol. 18, no. 6, pp. 1038–1068, 2017.

[165] A. Milioto, P. Lottes, and C. Stachniss, "Real-time Semantic Segmentation of Crop and Weed for Precision Agriculture Robots Leveraging Background Knowledge in CNNs," *arXiv*, pp. 2229–2235, 2017.

[166] A. EI-Kazzaz, "Soilless Agriculture a New and Advanced Method for Agriculture Development: an Introduction," *Agricultural Research & Technology:Open Access Journal*, vol. 3, no. 2, 2017.

[167] N. Sharma, Y. Khajuria, V. K. Singh, S. Kumar, Y. Lee, P. K. Rai, and V. K. Singh, "Study of molecular and elemental changes in nematode-infested roots in papaya plant using FTIR, LIBS and WDXRF spectroscopy," *Atomic Spectroscopy*, vol. 41, no. 3, pp. 110–118, 2020.

[168] Y. W. Kuo, C. L. Li, J. H. Jhang, and S. Lin, "Design of a Wireless Sensor Network-Based IoT Platform for Wide Area and Heterogeneous Applications," *IEEE Sensors Journal*, vol. 18, no. 12, pp. 5187–5197, 2018.

[169] I. Mat, M. R. Mohd Kassim, A. N. Harun, and I. Mat Yusoff, "IoT in Precision Agriculture applications using Wireless Moisture Sensor Network," *ICOS 2016 - 2016 IEEE Conference on Open Systems*, pp. 24–29, 2017.

[170] V. I. Adamchuk, J. W. Hummel, M. T. Morgan, and S. K. Upadhyaya, "On-the-go soil sensors for precision agriculture," *Computers and Electronics in Agriculture*, vol. 44, no. 1, pp. 71–91, 2004.

[171] S. Khanal, J. Fulton, and S. Shearer, "An overview of current and potential applications of thermal remote sensing in precision agriculture," *Computers and Electronics in Agriculture*, vol. 139, pp. 22–32, 2017. [Online]. Available: http://dx.doi.org/10.1016/j.compag.2017.05.001

[172] M. Pule, A. Yahya, and J. Chuma, "Wireless sensor networks: A survey on monitoring water quality," *Journal of Applied Research and Technology*, vol. 15, no. 6, pp. 562–570, 2017. [Online]. Available: http://dx.doi.org/10.1016/j.jart.2017.07.004

[173] Y. Liu, M. R. Langemeier, I. M. Small, L. Joseph, and W. E. Fry, "Risk management strategies using precision agriculture technology to manage potato late blight," *Agronomy Journal*, vol. 109, no. 2, pp. 562–575, 2017.

[174] B. Omoniwa, R. Hussain, M. A. Javed, S. H. Bouk, and S. A. Malik, "Fog/edge computing-based iot (feciot): Architecture, applications, and research issues," *IEEE Internet of Things Journal*, vol. 6, no. 3, pp. 4118–4149, 2019.

[175] S. Champion, Linsky, P. Mutschler, B. Ulicny, T. Reuters, L. Barrett, G. Bethel, M. Matson, T. Strang, K. Ramsdell, and S. Koehler, "Threats to precision agriculture (2018 public-private analytic exchange program report)," 02 2020.

[176] T. Huang, S. Yan, F. Yang, T. Pan, and J. Liu, "Building sdn-based agricultural vehicular sensor networks based on extended open vswitch," *Sensors*, vol. 16, no. 1, 2016. [Online]. Available: https://www.mdpi.com/1424-8220/16/1/108

[177] M. Ndiaye, G. P. Hancke, and A. M. Abu-Mahfouz, "Software defined networking for improved wireless sensor network management: A survey," *Sensors*, vol. 17, no. 5, 2017. [Online]. Available: https://www.mdpi.com/1424-8220/17/5/1031

[178] R. S. Alonso, I. Sittón-Candanedo, R. Casado-Vara, J. Prieto, and J. M. Corchado, "Deep reinforcement learning for the management of software-defined networks in smart farming," in *2020 International Conference on Omni-layer Intelligent Systems (COINS)*, 2020, pp. 1–6.

[179] Wikipedia contributors, "Q-learning — Wikipedia, the free encyclopedia," 2021, [Online; accessed 8-March-2021]. [Online]. Available: https://en.wikipedia.org/w/index.php?title=Q-learning&oldid=1007185643

[180] D. Vasisht, Z. Kapetanovic, J. Won, X. Jin, R. Chandra, S. Sinha, A. Kapoor, M. Sudarshan, and S. Stratman, "Farmbeats: An iot platform for data-driven agriculture," in *14th USENIX Symposium on Networked Systems Design and Implementation (NSDI 17)*. Boston, MA: USENIX Association, Mar. 2017, pp. 515–529. [Online]. Available: https://www.usenix.org/conference/nsdi17/technical-sessions/presentation/vasisht

[181] H. M. Jawad, R. Nordin, S. K. Gharghan, A. M. Jawad, and M. Ismail, "Energy-efficient wireless sensor networks for precision agriculture: A review," *Sensors (Switzerland)*, vol. 17, no. 8, 2017.

[182] R. K. Singh, R. Berkvens, and M. Weyn, "Energy Efficient Wireless Communication for IoT Enabled Greenhouses," *2020 International Conference on COMmunication Systems and NETworkS, COMSNETS 2020*, pp. 885–887, 2020.

[183] F. K. Shaikh and S. Zeadally, "Energy harvesting in wireless sensor networks: A comprehensive review," pp. 1041–1054, mar 2016.

[184] U. Mehboob, Q. Zaib, and C. Usama, "Survey of IoT Communication Protocols Techniques, Applications, and Issues," *Flow Research Inc, Pakistan*, pp. 1–80, 2016.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3116814, IEEE Access

[Online]. Available: http://xflowresearch.com/wp-content/uploads/2016/02/Survey-of-IoT-Communication-Protocols.pdf

[185] C. Benavente-Peces, "On the energy efficiency in the next generation of smart buildings—supporting technologies and techniques," *Energies*, vol. 12, no. 22, pp. 1–25, 2019.

[186] R. K. Singh, R. Berkvens, and M. Weyn, "Time synchronization with channel hopping scheme for lora networks," in *Advances on P2P, Parallel, Grid, Cloud and Internet Computing*, L. Barolli, P. Hellinckx, and J. Natwichai, Eds. Cham: Springer International Publishing, 2020, pp. 786–797.

[187] J. J. Estrada-Lopez, A. A. Castillo-Atoche, J. Vazquez-Castillo, and E. Sanchez-Sinencio, "Smart Soil Parameters Estimation System Using an Autonomous Wireless Sensor Network with Dynamic Power Management Strategy," *IEEE Sensors Journal*, vol. 18, no. 21, pp. 8913–8923, 2018.

[188] K. Goel and A. K. Bindal, "Wireless sensor network in precision agriculture: A survey report," *PDGC 2018 - 2018 5th International Conference on Parallel, Distributed and Grid Computing*, pp. 176–181, 2018.

[189] F. Kiani and A. Seyyedabbasi, "Wireless sensor network and Internet of Things in precision agriculture," *International Journal of Advanced Computer Science and Applications*, vol. 9, no. 6, pp. 99–103, 2018.

[190] N. Ahmed, D. De, and I. Hussain, "Internet of Things (IoT) for Smart Precision Agriculture and Farming in Rural Areas," *IEEE Internet of Things Journal*, vol. 5, no. 6, pp. 4890–4899, 2018.

[191] X. Feng, F. Yan, and X. Liu, "Study of Wireless Communication Technologies on Internet of Things for Precision Agriculture," *Wireless Personal Communications*, vol. 108, no. 3, pp. 1785–1802, 2019. [Online]. Available: https://doi.org/10.1007/s11277-019-06496-7

[192] A. A. Madushanki, M. N. Halgamuge, W. A. Wirasagoda, and A. Syed, "Adoption of the Internet of Things (IoT) in agriculture and smart farming towards urban greening: A review," *International Journal of Advanced Computer Science and Applications*, vol. 10, no. 4, pp. 11–28, 2019.

[193] P. P. Ray, "Internet of things for smart agriculture: Technologies, practices and future direction," *Journal of Ambient Intelligence and Smart Environments*, vol. 9, no. 4, pp. 395–420, 2017.

[194] R. Rayhana, G. Xiao, and Z. Liu, "Internet of Things Empowered Smart Greenhouse," *IEEE Journal of Radio Frequency Identification*, vol. 7281, no. c, pp. 1–1, 2020.

[195] Y. E. Hamouda and B. H. Elhabil, "Precision Agriculture for Greenhouses Using a Wireless Sensor Network," *Proceedings - 2017 Palestinian International Conference on Information and Communication Technology, PICICT 2017*, pp. 78–83, 2017.

[196] A. Kochhar and N. Kumar, "Wireless sensor networks for greenhouses: An end-to-end review," *Computers and Electronics in Agriculture*, vol. 163, no. July, 2019.

[197] D. Popescu, F. Stoican, G. Stamatescu, O. Chenaru, and L. Ichim, "A survey of collaborative UAV-WSN systems for efficient monitoring," *Sensors (Switzerland)*, vol. 19, no. 21, pp. 1–40, 2019.

[198] K. Pallavi, J. D. Mallapur, and K. Y. Bendigeri, "Remote sensing and controlling of greenhouse agriculture parameters based on IoT," *2017 International Conference on Big Data, IoT and Data Science, BID 2017*, vol. 2018-Janua, pp. 44–48, 2018.

[199] C. Robles Algarín, J. Callejas Cabarcas, and A. Polo Llanos, "Low-cost fuzzy logic control for greenhouse environments with web monitoring," *Electronics*, vol. 6, no. 4, 2017. [Online]. Available: https://www.mdpi.com/2079-9292/6/4/71

[200] S. Maurya and V. K. Jain, "Fuzzy based energy efficient sensor network protocol for precision agriculture," *Computers and Electronics in Agriculture*, vol. 130, pp. 20–37, 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169916308250

[201] P. Fraga-Lamas, M. Celaya-Echarri, P. Lopez Iturri, L. Azpilicueta, P. Lopez-Iturri, F. Falcone, and T. M. Fernández-Caramés, "Design and Empirical Validation of a LoRaWAN IoT Smart Irrigation System Radio Propagation within Dense Vegetation environments View project Towards Smart Health Systems View project Design and Empirical Validation of a LoRaWAN IoT Smart Irrigation System," vol. 15, 2019.

[202] cioreviewindia, "20 most promising agriculture technology solution providers - 2018," 2018, [Online; accessed 1-Sep-2021]. [Online]. Available: https://agriculture.cioreviewindia.com/vendors/2018/0

[203] pinduoduo, "10 precision agriculture companies that are changing the farming industry," 2021, [Online; accessed 1-Sep-2021]. [Online]. Available: https://stories.pinduoduo-global.com/agritech-hub/precision-agriculture-companies

[204] plugandplaytechcenter, "10 precision agriculture companies to watch in 2019," 2019, [Online; accessed 8-March-2021]. [Online]. Available: https://www.plugandplaytechcenter.com/resources/10-precision-agriculture-companies-watch-2019/

[205] A. T. Braun, E. Colangelo, and T. Steckel, "Farming in the Era of Industrie 4.0," *Procedia CIRP*, vol. 72, pp. 979–984, 2018. [Online]. Available: https://doi.org/10.1016/j.procir.2018.03.176

[206] V. Saiz-Rubio and F. Rovira-Más, "From smart farming towards agriculture 5.0: A review on crop data management," *Agronomy*, vol. 10, no. 2, 2020.

RITESH KUMAR SINGH received the M.Tech degree in Information Technology with specialization in Wireless Communication and Computing (WCC) from Indian Institute of Information Technology, Allahabad India in 2012. He worked with LG and TCS research labs on the development of Internet of Things (IoT) solutions till 2017. He is currently pursuing a PhD degree at the imec-IDLab research group, University of Antwerp, with a focus on Energy efficiency in IoT. His work includes the deployment and characterization of low-power communication networks.

RAFAEL BERKVENS received the MSc Applied Engineering (Electronics-ICT) from the University of Antwerp, Belgium, in 2012 on laser range finder based travel distance estimation. He got his PhD (Applied Engineering) in 2017 on uncertainty in indoor localization based on electromagnetic fingerprints. He is currently working as Senior researcher in the IDLab UAntwerp team of Prof. Maarten Weyn, since 2017. He has expertise in localization and context awareness based on wireless communication.

MAARTEN WEYN received his Ph.D. in Computer Science on the topic of Opportunistic Seamless Localization from the University of Antwerp, Belgium. He is a Professor at the University of Antwerp, currently teaching the 3rd year bachelor courses Mobile Communication and Telecommunication and Master courses Communication Systems, and Internet of Things: Low Power Embedded Communication in the department of Applied Sciences: Electronics-ICT, and in the postgraduate Internet of Things, the course on Context Aware Wireless Embedded Systems. Maarten is instructor at the LoraWAN Academy on the topic of localization and lecturer in a few courses on Coursera on Embedded IoT systems. His research in the imec-IDlab research group focuses on ultra-low power sensor communication and embedded systems, sub 1-Ghz communication, sensor processing and localization. Most of his projects are in close collaboration with industry. He is the co-founder of the spin-offs Aloxy, CrowdScan en AtSharp, involved in the creation of the spin-offs 1OK and Viloc, director of the Dash7 Alliance, IARIA Fellow, and initiator of the Open Source Stack OSS-7.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/