IEEE Sensors Council

# Technologies Driving the Shift to Smart Farming: A Review

Nabila Elbeheiry , *Member, IEEE*, and Robert S. Balog , *Senior Member, IEEE*

Abstract—As today's agriculture industry is facing numerous challenges, including climate changes, encroachment of the urban environment, and lack of qualified farmers, there is a need for new practices to ensure sustainable agriculture and food supply. Consequently, there is an emphasis on upgrading farming practices by shifting toward smart farming (SF)—utilizing advanced information and communication technologies to improve the quantity and quality of the crop with minimal labor interference. SF has gained lots of interest in recent years utilizing a variety of technological innovations in the field, which imposes a challenge on farmers and technology integrators to identify suitable technologies and best practices for a particular application. This article provides a

survey of the most recent SF scientific literature to identify common practices toward technology integration, challenges, and solutions. The survey was conducted on 588 papers published on the IEEE database following Cochrane methods to ensure appropriate analysis and interpretation of results. The papers' contributions were analyzed to identify necessary technologies that constitute SF, and consequently, research themes were identified. The identified themes are sensors, communication, big data, actuators and machines, and data analysis. Besides presenting an in-depth analysis of each identified theme, this article discusses integrating more than one technology in systems to achieve independency. The most common SF systems are remote monitoring, autonomous, and intelligent decision-making systems.

Index Terms— Actuators, automation, data analysis, deep learning (DL), Internet of Things (IoT), irrigation systems, low-power wide area network (LPWAN), machine learning (ML), microcontrollers, remote monitoring, robotics, smart farming (SF), wireless sensor networks (WSNs).
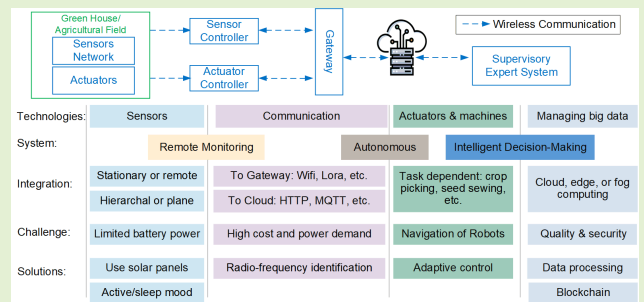
I. INTRODUCTION

ACCORDING to the Food and Agriculture Organization of the United Nations, "the world's population is expected to grow to almost ten billion by 2050, which requires a 60% increase in global food production" [1]. Meanwhile, food security is threatened by the increase in pests and diseases, lack of qualified labor, and climate changes [2], [3]. The rise in food demand and the challenges faced on the production side motivated the shift from traditional agriculture to smart farming (SF). SF refers to incorporating technologies in the field to either decrease human involvement or increase the quality and quantity of production yield [4].

SF and its literature have experienced an explosion in development that includes integrating cutting-edge technologies,

such as Internet-of-Things (IoT) devices, advanced actuation systems, and data analytics techniques. The increased volume of research literature has made it difficult for individuals to assess the vast quantity of work to identify suitable technologies and best practices for a particular technology. To this extent, there have been previous efforts to provide an overview of different technologies in SF, such as IoT [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], data analysis and machine learning (ML) techniques [14], [18], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], sensor networks [12], [17], [33], [34], [35], [36], [37], [38], and intelligent actuation systems [39], [40], [41], [42], [43], [44]. As those papers are technology-oriented, they focus exclusively on providing a technical overview of the domain and/or tracking the most recent advancements in a field, giving little to no awareness to nonspecialists on technology integration guidelines. Other general survey papers focused on identifying trends and patterns of research on SF [45], [46], [47] or highlighting the role of different technologies in the agricultural industry in a particular region [48], [49].

A limitation of previous literature reviews is that they target researchers and technology developers rather than farmers and practitioners. The contribution of this article is to provide guidance to SF practitioners by surveying the most recent

scientific literature and analyzing the technology integrated into SF. This article examines various integration options for each technology and highlights the key challenges faced during technology integration and the proposed solutions.

The remainder of this article is organized as follows. Section II presents the procedure followed to collect, organize, and analyze the literature. Section III shows an in-depth analysis of all technology integrated into SF literature, along with their key challenges and solutions. Section IV provide a discussion of systems that integrate multiple technologies.

II. METHODS

This study was designed in accordance with the Cochrane reporting methodology for systematic review guidelines. The Cochrane protocol was adopted as it guarantees highly structured and transparent research outcomes [50]. The methodology entailed identifying the research papers included in the survey, preparing the documents for in-depth analysis through an initial assessment, and then evaluating and analyzing the literature.

A search statement that fits a prespecified eligibility/inclusion criterion was applied to the IEEE database to find all relevant research papers. The inclusion criteria attempt to collate all documents that contribute to studying or applying new technology in the field of SF. To meet this criterion, a two-word search statement was used. The search statement comprised one word from each of the following sets: [*smart, precession, intelligent, advanced*] and [*greenhouse, farming, agriculture*]. Truncation symbols were used to ensure that plural forms and variant spellings were included in the results. The "all fields" option was selected in the search engine to ensure inclusiveness. In addition, the publication years were specified to be between 2015 and 2021. The choice of this particular period is justified by considering that SF is a new phenomenon, and the older literature could be misleading in describing the current state of the art and research.

The search statement was applied to the IEEE database to collect papers to be surveyed. The IEEE database was chosen for the quality and credibility of its scientific publications, as reflected by the 2020 Journal Citation Report [51]. In addition, the IEEE database provides access to a comprehensive source of bibliographic citations covering the scope of technologies in different fields, including smart agriculture. At this stage, 2300 papers were obtained. The selection of the IEEE as the only database was to balance time restraints and thoroughness. Using IEEE solely is justifiable as it is the most extensive database for advancing technologies that guarantee to identify sufficient eligible studies and ensure that there is no bias.

After an initial data set had been collected, a primary analysis has been performed to: 1) exclude irrelevant papers based on an exclusion criterion and 2) identify research themes. The exclusion criterion was set to ensure that any out-of-scope paper should be eliminated. The exclusion criterion was based on papers' contributions, and it included papers that are not related to farming and papers that tackle SF from a nontechnology perspective. Papers that are not related to farming included, but were not limited to, documents about
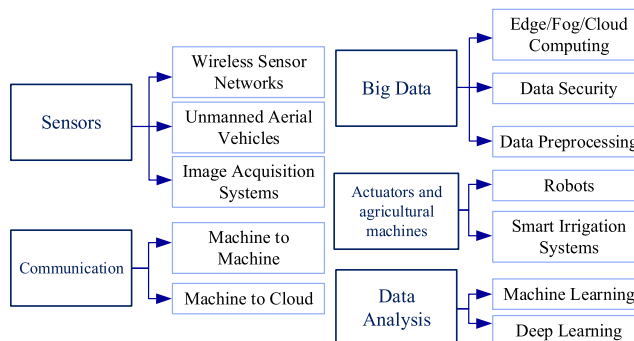

Fig. 1. Taxonomy of the SF literature.

wind and solar farms, smart cities, animal welfare monitoring, and greenhouse gas emissions. Other papers that tackle SF from an out-of-scope perspective discuss issues such as designing platforms that provide advice to farmers, connecting farmers with other food industry stakeholders (customers and retailers), and performing social studies related to SF. The exclusion criteria were manually applied to filter papers out. The irrelevant papers were filtered manually as adding the "NOT" option in the search criteria would have eliminated relevant papers. After filtering the irrelevant papers, the team was left with 588 papers.

To provide an integral view of the research activity in the field of SF, the primary analysis included assessing the papers to identify the technology they incorporate. After reviewing all documents, the most analyzed SF literature has provided research insight into one of the following themes: sensors, big data, communication, actuators and machines, and data analysis. Big data refer to techniques adopted to handle issues arising from the difficulties in storing, processing, and analyzing the enormous volume of data. After papers have been reviewed and tagged with them based on the technology that they incorporate, an exhaustive analysis was performed. All included studies were analyzed to draw a conclusion on all identified research themes in an impartial and objective way. Fig. 1 provides an insight into the structure of each of the themes found that will be analyzed holistically in this study.

While some of the literature researches implanting a single technology in the field, others show to integrate more than one technology to form a system. Fig. 2 shows the breakdown of literature in SF and their contribution to different themes and systems. Remote monitoring, automation, and decision support are examples of systems present in SF. Any of those systems would include at least two technologies. As seen in Fig. 2, the most dominant technology is sensors since they are the basis of any SF system. The numbers in Fig. 2 show that some papers do not fit in any of the identified themes, while others fall into two or more categories.

III. ANALYSIS: ENABLING TECHNOLOGIES

A. Sensors

Sensors are integrated into SF to gather data for various reasons, including, but not limited to, environmental monitoring, crop quality monitoring, and fertilizers' control. The deployment of sensors typically takes the form of sensor nodes and
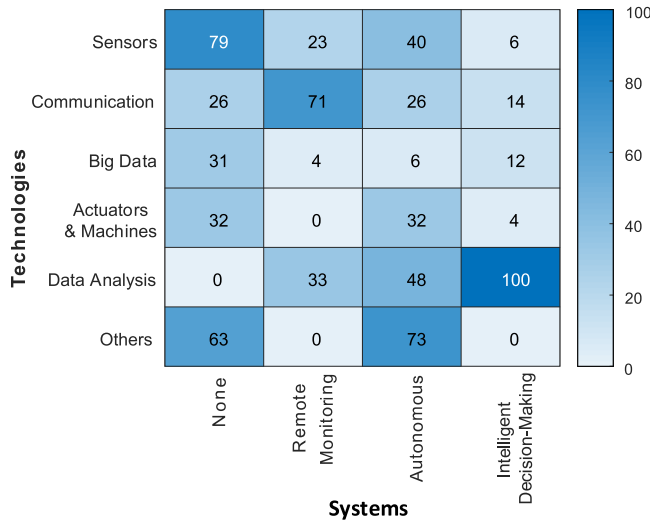
Fig. 2. Heatmap of the SF literature.

TABLE I
COMMERCIAL OF THE SHELF SENSOR MODULES
USED IN THE SF LITERATURE

Phenomena	Module	Comments / Description	Ref.
Air temperature	LM35	Output voltage is linear among the Celsius.	[89, 90]
	DS18B20	Waterproof temperature sensor	[91]
Air temperature & humidity	DHT11	It is a digital sensor with digital calibrated outputs.	[91-93]
	DHT22	It digital sensor that uses a capacitive humidity sensor and a thermistor.	[94-96]
	AM2303	It is a digital sensor with digital calibrated outputs.	[95, 97]
	SHT75	It is a digital sensor that uses a unique capacitive sensor to measure humidity and a band-gap sensor to measure temperature.	[98]
	SI7006-A20	It uses low-K polymeric dielectrics for sensing humidity	[99]
Atmospheric pressure	BMP085	It uses I2C interface with the microcontroller.	[95]
	MPL3115 A2	It uses I2C interface with the microcontroller.	[99]
Air quality	MQ-135	It is capable of sensing the presence of various gases.	[100]
light intensity	BH1750	It provides digital signal output with accuracy of 1Lux.	[95, 97]
	LTR 329ALS-01	It is an I2C digital sensor, which converts the light's intensity into a digital signal output.	[99]
Ultraviolet light	ML8511	It ouptus analogue proportional to the amount of Ultraviolet light.	[95]
Solar radiation	SP-110	It is self-powered, analog sensor.	[98]
Wind Speed	A3144	It uses hall effect.	[101]
Soil moisture	VL95	Resistive soil moisture sensor.	[89]
	FC-28	Capacitive soil moisture sensor.	[100]
Soil Conductivity	SEN0114	Resistive soil moisture sensor.	[102]
Soil temperature	DS18B20	It delivers a high-resolution digital output.	[96]
	SHT10	It delivers a high-resolution digital output.	[102]
Soil and water pH	SEN0249	It outputs a voltage signal that is proportion to the PH	[101]
Water level sensor	PN121102 15TC-8	Its output resistance is is proportional to the liquid level.	[103]
	HC-SR04	It uses ultrasonic .	[101]

groups of synchronized sensors that collect data and send it to a destination through wireless communication. A sensor node typically consists of sensors, a battery, a controller, and a transceiver. A group of connected sensor nodes is referred to as a wireless sensor network (WSN). This section focuses on sensors and sensor node topologies, including key challenges and solutions related to deploying sensors in SF.

1) Sensor Modules: Few papers discuss novel sensing techniques [52], [53], [54], [55], [56], [57], [58], [59] or sensors' fabrication [60], [61]. The majority of literature uses commercial off-the-shelf sensor modules. Table I lists examples of sensors for environmental and soil-related measurements. The sensors listed in Table I have different measuring ranges, accuracies, and prices. Practitioners need to choose sensors that work best for their applications. An algorithm that optimizes sensor selection for a given application has been proposed [62].

2) Sensor Nodes' Placement and Interconnection in a WSN: Sensors placed in an agricultural field can be either stationary or remote. Remote sensors can be accomplished in the air through the use of a flying drone [63], [64], [65], [67] or on the ground via a patrolled vehicle [68], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83]. The choice between stationary and remote sensor networks comes with a tradeoff between flexibility and cost as stationary uses a fixed sensing grid, which limits reconfigurability but lower implementation and use cost. A mobile system can adapt to changing uses but has higher implementation and use costs.

To guarantee the best coverage area for stationary sensors, a design process, which ensures that sensors are optimally placed, has been utilized. Typical design considerations for static sensors include choosing the sensor locations infield and setting a sensor network architecture. The two approaches for placing sensors are equal-distanced sensor placement [84], [85], [86], [87] and the trial-and-error method [84]. While the former is more common, the latter results in more accurate measurements but a longer design process [84].

A computational model that ensures strategic deployment of the equal-distanced sensor was developed in [55].

Compared to stationary sensors, remote sensors can provide a more accurate representation of the field conditions—i.e., better ability to detect microclimates—with fewer sensors. However, battery life is an important issue that limits the flight time of drones and other mobile platforms. Also, remote sensing needs a navigation system. This can be autonomous, such as unmanned aerial vehicles (UAVs) [68], or may require an operator [88]. Autonomous navigation systems are computationally extensive and would require additional spatial measurements.

Sensor network architecture is concerned with connections between sensors and other components to ensure optimal network configuration. Plane and hierarchal architecture are two common architectures implemented in the SF literature. A plane architecture is where all nodes have the same status,

abilities, and roles. On the other hand, a hierarchal structure involves having more superior nodes responsible for collecting and forwarding data. A plane structure is more straightforward and less affected by an individual node's failure. However, it is impractical in a larger network as it will demand extensive energy [104]. A two-level node hierarchal structure is more common [85], [105], [106] where the first level (slave nodes) senses and sends the data to a more advanced node (referred to as a sink or a master node) that sends data to an external source and coordinates the slave nodes. A group of slave nodes managed by a master is referred to as a cluster, and the master is the cluster head. Clustering sensors to form nodes can be done by grouping like sensors together and powering them with different sources according to their different needs [107] or making each node heterogeneous to ensure similar power demand among nodes [108]. The first is easier to design and requires less human work for battery replacements; however, it might be more expensive. Methods for calculating the sensor nodes' energy demand are presented in [108] and [109].

3) Challenges: A technical concern when deploying a WSN is energy. In a WSN, the energy is constrained to the capacity of the battery powering them. The entire sensor node fails once the battery is depleted and not recharged or replaced [110], [111]. Hence, minimizing the power consumption of the sensor nodes is critical. It is also possible to harvest ambient energy to power the sensor node. To reduce the power consumption of the sensor node, research utilizes methods that switch the nodes [107], [112], [113] or their transceivers (most power-hungry block) [85], [114] OFF when not used. This is also known as putting nodes in the sleep mode. The sleep time can occur at prescheduled fixed intervals [107] or event-based such as to report changing weather conditions [85] (i.e., a rainy, cloudy day would require more awake time than a typical summer day).

The fixed-interval sleep mode saves energy but risks missing data instances when the node is OFF. Also, the setup time taken by the transceiver once it wakes up leaves the node more vulnerable to transition delays. Another power-saving method is to continuously reconfigure the data routing paths (reassigning master and slave nodes) [108], [115], [116]. The operating principle of those methods is to develop an algorithm that keeps changing the master node, since it is the most energy-intensive, to give all nodes a longer lifetime and guarantee that all nodes will be depleted together.

Reducing the quantity of data that need to be transmitted is important for minimizing power [117]. Spatial data compression (nearby nodes talk to check repeated patterns in the data) has been used to lower the amount of transmitted data [117]. Although data compression requires some additional computations at the node level, it was shown that the computation power is much less than the power for long-distance communication [117]. Power saving has also been achieved using a low-power microcontroller (e.g., MSP430FR5969 and ESP8266EX) that offers increased performance at a lower energy budget [102], [118], [119].

Power consumption and battery life shape a burden in remote sensing platforms. That is, since using the traditional battery charging stations has an impact on mobility, alternatively, replacing the battery when depleted requires additional manual work and higher initial investment as one would need spare batteries. To this extent, wireless power transfer has been investigated to overcome this burden [73], [120], [121]. Solar energy harvesting has also been deployed in the literature to solve the limited power available to sensor nodes [102], [118], [122], [123]. An additional power converter accompanies the integration of solar energy to regulate the power supply and the battery charging. BQ25570 IC is an example of a commercialized power regulator used [102], [124]. Another energy harvesting technique that overcomes the limitations of solar, being weather dependent, is using the radio frequency (RF) signal to provide energy to the sensor node [125].

A second challenge faced is the risk of losing data due to power loss or failure of components. To mitigate this risk, IdealVolting, a technique used to explore the possibility of operating below the minimum power specifications without compromising the measurement [126], has been studied. Moreover, the literature investigates using ML to predict the data to interpolate missing points [98], [127], [128]

B. Communication

The advances in the communication field and the IoT architectures have resulted in many protocols that can be utilized in SF, leaving flexibility for users' selections depending on their needs and constraints. Generally, the pattern followed is using two communication pathways.

1) Machine-to-Gateway (M2G): Communication back and forth between sensors or actuators nodes and microcontrollers.

2) Machine-to-Cloud Communication (M2C): Passing data through the transmission control protocol/internet protocol (TCP/IP) network to a final destination.

The choice of data transmission platform is subject to many constraints, including available bandwidth, the required transmission rate, latency, data volume, and reliability. This section discusses the used protocols and challenges faced when designing a communication network.

1) M2G Communication Protocols: Various protocols have been utilized to establish M2G communication, including: 1) standard protocols, such as Zigbee [77], [129], [130], [131], [132], [133], [134], [135], Bluetooth [136], [137], 138], Wi-Fi [89], [90], [139], [140], [141], cellular networks [110], [129], [130], [131], [133], [142], and RF identification (RFID) [95], [121], [143], [144], [145], [146] and 2) low-power wide area networks (LPWANs), such as LORA [147], [148], [149], [150], [151], [152], [153], [154], [155], NB-IoT [156], [157], and Sigfox [99], [158], [159].

RFID is an energy-efficient communication technique, but it has a limited coverage area. Zigbee is based on an IEEE standard and can be connected easily through an Xbee module. The advantage of Zigbee is its low cost and low power consumption. However, Zigbee is limited in terms of data rate and coverage area. Wi-Fi and Bluetooth are alternatives that offer improved data rates. Bluetooth connection can be established by attaching the HC-05 module to the Arduino [128], [130], while Wi-Fi can be through the ESP8266 [132], [133], [134] module or directly through the Raspberry Pi with

a built-in Wi-Fi module. The main limitation of Wi-Fi and Bluetooth is their narrow coverage area, which is overcome in cellular networks that offer high-speed communication and a wide coverage range. The SF literature has captured the most recent advancements in the cellular network to increase the transmission data rate as in [110], which utilizes the critical techniques in 5G to accommodate more sensor nodes and prolong the lifetime of the WSNs. However, the use of cellular networks consumes more energy.

LPWAN is a set of emerging network protocols capable of transmitting data over a long distance (couple of kilometers) with relatively lower power to overcome standard network limitations. The most common LPWAN protocol, in SF, is LoRaWan, an open-access protocol that uses LoRa technology. To set up an LoRaWan network, one can use a microcontroller that supports an LoRa module, such as Arduino Uno that works with the LoRa/GPS shield [160] or the STM32F103 that is compatible with the Lora module Ra01 [161]. Setting up the LoRa network requires calibration of the sender and receiver antenna gain [160]. NB-IoT is another LPWAN technology that offers more coverage area than LoRa [156], and it can be integrated through the SIM7020, which can be connected to a Raspberry Pi [157]. Sigfox has also been utilized in SF through the Sigfox ship, SFM11R2D [158], or the Sigfox Shield for Arduino (UNASHIELD-V2S) [159]. The main drawback of LPWAN is that it has a relatively low data rate in comparison to other traditional protocols. The low data rate makes utilizing LPWAN impractical for high density of sensors. A solution to mitigate this drawback is to utilize a multichannel gateway [152]. Another drawback of LPWAN is the risk of data collision when two nodes are sending data simultaneously. This challenge has been addressed in [161] by allocating independent time slots for transmission for each node. The solutions proposed to overcome LPWAN limitations increase power consumption; hence, optimization is needed between power consumption, coverage area, and data rate.

2) M2C Communication Protocols: On the other hand, the most common method to establish M2C communication in SF is to connect the microcontroller to the local wireless network connected to the Internet. Alternatively, some papers use the hypertext transfer protocol (HTTP) [89], [162], the message queue telemetry transport (MQTT) [97], [163], [164], or the constrained application protocol (CoAP) [165], TCP/IP protocols that are used to establish M2C communication, known as IoT protocols.

3) Challenges: The limited resources assigned to the devices' communication create challenges in deploying communication networks. In other words, the challenge associated with designing a communication network is the desire to achieve a firm, reliable, and fast data delivery while optimizing factors such as power consumption, cost, and coverage area. Unfortunately, the literature did not state one solution that fits all. Hence, SF integrators should explore existing solutions and choose according to their application requirements. This section demonstrates an overview of the commonly used communication protocols, there are many other factors to be considered. For instance, the performance can drastically if deployed indoor or outdoor, urban, or rural, and many other

factors. Detailed comparisons are available in [158], [166], [167], [168], and [169].

C. Actuators and Machines

In agriculture, robotics has been applied to various fields of agriculture. The SF literature that focuses on robotics revolves around two issues. The first is designing new robots that perform tasks in the field. The second is to improve the performance of existing irrigation machines.

1) Robots: The literature used robots for multiple purposes, including spraying or removing pesticides [170], [171], [172], [173], irrigation [174], [175], picking crops [171], [176], [177], sewing seeds [178], [179], [180], plowing soil [181], [182], and harvesting [162], [183]. Robots' design and development considerations include controlling robots, and their parts' movement [162], [184], [185], selecting and integrating motors [180], [186], and the mechanical design of the body/chaise [174], [181], [186], [187] are discussed design issues. The most common method to track the movement's motion is utilizing an ultrasonic sensor [171], [174], [181], [182]. As for the motors, dc [175], [176], [181], [188] and servo [172], [181], [182], [189] motors are the most common motors used. In addition to the robots' design considerations, achieving long-term autonomy is a significant challenge. Although advanced control methods exist in different applications, the nature of agricultural fields (vast and numerous arrangements of crops) makes it challenging. To address the challenge of robots' motion, adaptive motion control strategies have been proposed [73], [190]. Those strategies showed significant improvement over methods that require detailed field information.

2) Irrigation System: As irrigation is the basis of agriculture, the literature has explored methods to achieve efficient automatic irrigation. The most straightforward practice for automating the irrigation system is using pipes controlled via a solenoid valve [103], [191], [192], [193]. A solenoid valve is an electromechanical device that can be switched by a relay placed on solenoid power cables. Using a solenoid valve solely might not be adequate for applications that need applied pressure for water transfer. Hence, water pumps have been used for irrigation in SF [119], [194], [195]. Pumps allow more flexibility in the system design; however, they demand more energy. To overcome limited energy, solar-powered irrigation systems [196], [197], [198], [199], [200] or passive irrigation systems have been studied. Passive systems use pressure-generated columns derived from the water potential to actuate the valve [201] or utilize the siphon concept [202]. While those systems do not demand any power, they are adequate for limited-field architectures. Hence, there is a tradeoff between design flexibility and power consumption.

3) Challenges: The challenge faced while designing an SF irrigation system is the limited amount of water available in some fields. The research explored methods to minimize water consumption, including reusing wastewater (recycling) [196], [202], [203] to overcome this challenge. Another water conservation approach is to adopt water management schemes to minimize unnecessary watering of the crops [101], [200]. Also, using drip irrigation reduces the amount of water used

as it is proven to be the most water-efficient irrigation method [168], [196], [199], [200].

D. Managing Big Data

The enormous volumes of data captured by sensors in SF motivate addressing big data management in the literature. Managing big data is a discipline concerned with using techniques, tools, and platforms to address storage, preprocessing, processing, and security challenges. This section discusses the challenge of handling big data and presents the techniques adopted to mitigate those challenges.

The most significant challenge when dealing with big data is the extensive processing power and memory needed for its storage and processing. To deal with the limited processing and storing capabilities, most literature chooses to send data to a central cloud designed to manage a huge amount of data. Thing speak [89], [134], [137], [203], [204], [205], [206], Ubidots [94], Blynk [207], [208], OneNet [209], Amazon web services [100], and GoogleColab [210], [211] are examples of free IoT cloud services. The advantage of using those cloud services is the ease of integration. In addition, most clouds are accompanied by a dashboard that provides real-time data visualization and can easily be configured to user interfaces (web services or mobile applications). However, sending data to the cloud is accompanied by costs inherited from the data transfer and latency due to the time taken to send signals.

To reduce the cost inherited with the transfer, Gia et al. [155], Alonso et al. [212], and Ribeiro et al. [213] proposed methods of filtering data at the edge, sending only useful data to the cloud. Alternatively, computational and data storage procedures can be brought closer to the sensor or actuator node by utilizing existing devices' capacity (known as edge or fog computing) [206], [214], [215], [216], [217]. Unlike cloud computing, a single node having infinite capabilities, edge and fog computing deploy multiple distributed nodes with limited computational abilities and require resource management to ensure proper deployment. To address this issue, resource management techniques optimize the use of resources at the edge and guarantee fulfilling the application needs [212], [215].

Another challenge faced is the deterioration of data quality due to their exposure to cybersecurity attacks or accusation and transmission faults, leaving missing and inconsistent data. To handle this problem, papers implemented blockchain technology to ensure data privacy and authenticity [218], [219], [220]. Darkweb technology has also been used to boost the performance of blockchains as it avoids exposure to malicious denial of service attacks [221]. Another method used to enhance the security of the data is implementing access control systems to ensure that only authorized users can control the data [222], [223]. The later problem has been solved by utilizing techniques to identify uncertainties or noise in the data and mitigate them. Algorithms based on the Boltzmann ML [224], the Kalman filter [225], and the longest common subsequence (LCSS) [226] have been utilized for data processing. Enhancing the quality of data has also been achieved through interpolation models based on fuzzy

and neural network (NN) technology [128] and the anomaly detection algorithm based on matching old and new data [227].

E. Data Analysis

1) Machine Learning Techniques: As SF advances, ML techniques are widely adopted due to their potential to achieve reliable solutions to complex problems. Those techniques provide useful insight into the massive data generated by sensors through analyzing patterns and identifying trends. This section presents applications of data-driven decision-making in SF.

ML is the process of using data to acquire a model that represents the SF system and predicts its outcome. Broadly, ML in SF can be classified into regression and classification. Regression algorithms are used to find the relationship between continuous variables, while classification algorithms are concerned with determining class membership. The functionality, complexity, and data required for those algorithms vary significantly.

Simple regression algorithms—including linear, extreme gradient boosting (XGBoost), and stacked regressors—have been utilized to estimate the crop yield [228], [229], [230]. Decision tree, K-nearest neighbors (KNNs), random forest, naïve Bayes classifier, and support vector machine (SVM) are simple classifiers used to predict the most suitable crop for a region [210], [231], [232], [233], [234], [235], [236]. The simplicity of those algorithms enables presenting the relationship between data without demanding extensive computation power and, hence, can be employed at the edge. On the other hand, those models are incapable of doing more complex functions; hence, they have limited applications.

With the development of more advanced computing approaches, deep learning (DL) became the mainstream approach. DL utilizes NN models, the network of simple information processing units (known as neurons), to model complex relationships and extract features from huge datasets. The connection between neurons has a weight associated with them, which assigns a weighted sum to inputs of the neuron, and then, the resulted sum is passed through an activation function that determines the neuron's final output value.

NN has been used in SF for different purposes including soil or atmospheric parameter forecasting [98, 237, 238], optimal Environmental Conditions prediction [239], and artificial neural networks (ANN) based controller to optimize irrigation [240]. The desire of achieving tasks is to produce accurate results using NN, while minimizing the training time made the literature use tailored architectures, such as recurrent NNs (RNNs) and convolutional neural networks (CNNs). RNN has a memory buffer that stores the output of hidden layers and feeds it back to itself along with the upcoming input. This buffer makes RNN more suitable for processing sequential data. The ability to take the sequential information into consideration made RNN suitable for forecasting crop yield [241]. CNNs are tailored for image recognition tasks as neurons in an early layer of the network would extract local visual features, and neurons in later layers would combine these features to form higher order features. CNNs proved high accuracy in feature extraction in different SF applications, including
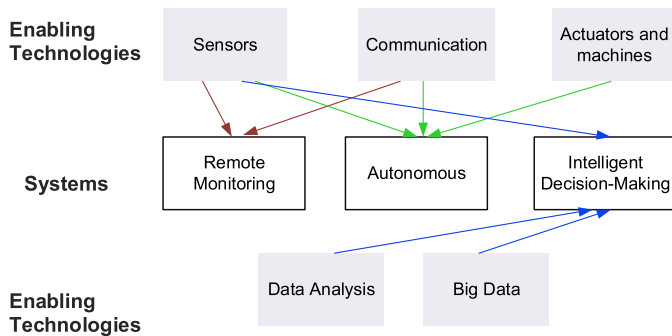
Fig. 3. Breakdown of SF systems.

detecting and diagnosing diseases, and weed-infected areas [242], [243], [244], [245], [246], [247], [248], [249], [250], determining the plants' quantity [92], [234], and detecting animals' intrusion [251].

2) Challenges: One of the challenges faced when applying ML in SF is the ability to find sufficient data to train the model. Finding a large data set that contains all possible usual conditions (anomalies) is a prerequisite for the success of the ML. To overcome this limitation, the literature utilized different sources, including weather repositories [217], [252] and image databases [246], [253], besides data collected in the field to train the ML model. However, an online task-oriented dataset might not be available. Another approach is to use data augmentation techniques to create new instances of data from the existing ones [248].

Another challenge faced is the noise in datasets, which might be misleading if used to train the ML model. Noisy data have been removed by experts in [254]. Alternatively, Kalman filtering to smooth the data [255] has been used. The high computation power and long training time of NNs shape a burden. To overcome this, papers integrate transfer learning, a technique that adjusts a model trained for a different task instead of training from scratch [211], [244], [253], [256], [257]. Transfer learning proved to obtain effective results at reduced cost using the pretrained model.

IV. TECHNOLOGY INTEGRATION INTO SYSTEMS

Numerous papers focused on integrating two or more of the aforementioned technologies to create an independent system. Among those systems, remote monitoring and autonomous, and discoing-making are the most common. Fig. 3 shows the enabling technologies used in forming each system.

A. Remote Monitoring Systems

Remote monitoring systems (RMSs) collect data from the physical layer (sensors and actuators) and send it to users through a visualization service (e.g., mobile app) and/or store data on a database server for further analysis. RMS provides the opportunity for farmers to observe the state of their farm, while he is away at any moment. Setting up an RMS requires the interconnection of a sensor network, a communication network, and a monitoring platform.

Due to the varying farmers' capabilities and demands, the RMS architecture did not converge. Its complexity ranges from a single sensing node that delivers data locally to multiple node systems that include an Internet connection to send data

to a back-end IoT system. The former system operates on an internal application running on the same server, which has been achieved through deploying the global system for mobile communications (GSM) network and sending short message/messaging service (SMS) to users [189], [258], [259] or through a mobile application that receives data via Bluetooth [136]. The advantage of a local system is that it does it require an Internet connection from the farmer. This is vital in the case of an emergent message being delivered, such as fire. Having no Internet connection is also preferred in some developing countries where Internet availability is not guaranteed. However, the GSM network that can send a limited amount of data makes it impractical for applications requiring the exchange of huge data amounts. The latter system, which is more common, utilizes the IoT concept (exchanging data through the Internet), which can be done by directly connecting the sensors to the TCP/IP network or through a middle layer, as shown in the communication techniques in Section III-A. The gateway can be any device composed of a CPU and equipped with a transceiver compatible with the used communication protocol. Raspberry Pi is the most common gateway. A sample of different IoT solutions is shown in Table II.

B. Autonomous Systems

Autonomous systems have recently drawn researchers' attention because of the advantages that it brings to the farm, including eliminating the need for manual work and saving a significant amount of water [94], [261]. The most common autonomous system discussed in the SF literature is the irrigation system. Other autonomous systems include controlling the temperature using cooling fans [135], [194], [262], heating fans [135], skylight opening [263], wet curtains [264], or bare tube heating systems [265], controlling light intensity using shutters [194] or artificial lights [135], [262], [266], [267], [268], and controlling humidity using water fans [269] or fogging system [268]. Also, systems that automate additives such as adding nutrient solutions [270], [271] or pesticides [272] in water or injecting carbon dioxide in the air [273] have been considered in the literature. The design process of the above autonomous systems involves developing control logic and hardware to operate the actuators along with elements discussed in Sections III-A–III-C: connectivity of sensors, local data transmission, and actuators. The link between the system components requires synchronization to ensure flawless operation.

Control logic is an algorithm that generates instructions to switch actuators, usually through acquiring and analyzing sensors' data. Time-based [274], [275], farmer-based [91], [270], [276], limit-based, and model-based are the classes of control logic implemented in the SF literature. Time- and farmer-based methods do not use sensors' readings as they control the actuators according to scheduled time slots or instructions from farmers. Limit-based is the most common with a predefined threshold. The output of the limit-based can either be binary (ON/OFF) [204], [226], [277], [278], [279], [280], [281] or, more flexibly, fuzzy [194], [266], [282], [283], [284], [285], [286], [287], [288], [289], [290], [291]. Model-based algorithms take actions in accordance with a reference

TABLE II
DIFFERENT ARRANGEMENTS FOR RMS

Ref.	Sensing Node			Communication Network		Back-end IoT system
	Sensors		Controller Board	From sensors	From Gateway	
[89]	Air temperature	LM35	Arduino UNO	Wi-Fi	HTTP	ThingSpeak Cloud
	Soil moisture	VL95				
[91]	Air temperature & humidity	DHT11	Arduino Mega2560	Wi-Fi	Direct link (no gateway)	Firebase Cloud
	Air temperature	DS18B20				
	Light intensity	LDR				
[92]	Soil moisture	DHT11	MCP3008	Xbee	MQTT	Google Cloud
	Light intensity	LDR				
[260]	Soil moisture	YL-38	Arduino	Wi-Fi	Direct link (no gateway)	Thing speak Cloud
[94]	Air temperature & humidity	DHT22	Raspberry Pi & ADS1115	Wi-Fi	Direct link (no gateway)	Ubidots Cloud
[97]	Air temperature & humidity	AM2303	STM32F103c8t6	LoRa	MQTT	Baidu Cloud
	Soil temperature & humidity	SMTS-II-485L				
	Light intensity	BMP180				

model, which can be based on scientific equations [101], [292], [293] or on previous data (i.e., ML models) [163], [239], [268], [294], [295], [296]. The fuzzy-based algorithm is preferred over other control algorithms as it enables multiple control variables without using more complicated mathematical or database models. Achieving the desired status of the actuators generated by the control logic has been done in the SF literature through two different hardware arrangements. One is by adding a hardware interface between the microcontroller and actuators. The second is using designated controllers that directly connect to the actuators. Relays [96], [142], [207], [233], [267], [271], [279], [292], [297], [298], [299], [300], [301], [302], transistors [303], and motor drivers [205], [261] are examples of blocks that operate in conjunction with the microcontroller. An alternative arrangement is replacing the microcontroller and the additional hardware with a programmable logic controller (PLC) [272], [286], [304]. PLCs can be programed to complete the entire automation process as their input can be connected to sensors, and their output can be connected to the actuators. PLCs are simpler to set up and program than combining a microcontroller with a hardware interface. However, they are more expensive and enable less freedom for the onboard control logic.

C. Intelligent Decision-Making Systems

Making decisions through sensors embedded in the field, data analysis techniques, and methods of handling big data has reshaped agricultural practices. Intelligent decision-making systems are included in all SF stages, starting from preplantation to postplantation activities. Predicting which crop suits the given environmental conditions and estimating expected crop yield are examples of preplantation decision-making. Decision-making during the plantation process includes identifying plant diseases, recognizing pests, and providing optimal nutrients and irrigation needs. Postplantation decision-making is concerned with counting and classifying crops. The high computation power and long training time of NNs shape a burden. To overcome this, papers integrate transfer learning, a technique that adjusts a model trained for a different task instead of training from scratch [211], [244], [253], [256], [257]. Transfer learning proved to obtain effective results at reduced cost using the pretrained model.

Table III summarizes all decision-making systems utilized in the literature. Table III shows that the most common decision-making system is the disease detection systems. Intelligent disease detection systems also provide the benefit of early detection and diagnosis, which can minimize losses. Weed detection and finding plants' needs are the literature's second and third most common decision-making systems. All those systems rely on plant pictures to extract features (e.g., color, size, morphology, and texture) and then classify them. The most common ML technique used is CNNs, as it has proved to produce accurate results for feature extraction and object classification. The high accuracy of CNN comes at the cost of demanding higher processing power and more extensive data volumes that are not always affordable. To overcome the limitations of CNN, many papers integrate transfer learning, a technique that adjusts a model trained for a different task instead of training a model from scratch or other ML techniques with CNN.

The high computation power and long training time of NNs shape a burden. To overcome this, papers integrate transfer learning, a technique that adjusts a model trained for a different task instead of training from scratch [211], [244], [253], [256], [257]. Transfer learning proved to obtain effective results at reduced cost using the pretrained model.

Table III also lists various sources of data in SF. The selection of the data source is a significant concern as it is a prerequisite for the success of the ML approach. Finding the appropriate data source is challenging because most ML algorithms need to be trained on a large dataset to optimize many parameters. In addition, supervised ML methods require the labeling of the data set, which requires a large amount of the experts' work. Given those challenges, four sources of data were used in SF literature: 1) installed sensors; 2) weather stations collecting meteorological data; 3) online databases; and 4) agricultural reference material.

V. DISCUSSION

The main observation of surveying papers on SF is that none of the solutions is satisfactory for all SF applications. Hence, practitioners need to choose the one that fits their needs and obliges them to their constraints. For instance, sensor integrators need to consider the cost, power consumption, and

TABLE III
INTELLIGENT DECISION-MAKING SYSTEMS IN SF

	Application	Data analysis approach	Data Source	Ref.
Pre-plantation	Predict crop yield	KNN, regression, and Decision Tree	Online database and on-site sensors	[228]
		Naive Bayes Gaussian classifier	Online database	[210]
		SVM and Decision Tree	on-site sensors	[235]
		Regression	Production report	[229]
	Determine plants' quantity	CNN	Images captured on-site	[92, 234]
During-plantation	Detect animals'	CNN	Images captured on-site	[251]
	Detect and/or diagnose diseases	NN and SVM	Images generated by drones and satellites	[247]
		Quantized CNN	Online database	[248]
		Residual Network and CNN	Images captured on-site	[305]
		CNN and TL	Images captured on-site	[211]
		TL	Images captured on-site	[256]
		Science-based	None	[306]
		CNN	Online database	[242]
		CNN	Images captured on-site	[243]
		CNN and Regression tree classifies	Data from online database	[307]
		DL	Online database	[253]
	Identify diseases severity	CNN and TL	Images captured on-site	[244]
		DL	Limited color images	[245]
	Identify weed infested region/ pest identification	CNN	Images captured on site	[246]
		CNN	Images captured on site	[249]
		CNN	Images captured by unmanned-aerial-vehicles	[250]
		CNN	Image captured on site	[308]
	Determine crop needs	Logistic regression	on-site sensors	[100]
		TL and NN	on-site sensors	[163]
		NN	Online Database and on-site sensors	[217]
	Forecast environmental variables	Neural Network	on-site sensors	[309]
		Regression	Meteorological data	[310]
		CNN	Image captured on site	[311]
	Identify growth stage	Self-Organizing Map, and K-means	Image captured on site	[312]
		Viola and Jones	Images captured on site	[313]
		CNN and TL	Images captured on site	[314]
	Detect faulty actuators	Gaussian mixture model	Videos recorded on site	[315]
		CNN and Hough transform	Images captursed on site	[316]
	Count Plants	TL	Online Database	[257]

design complexity while choosing the sensor types, quantity, and placement methods. As for the communication network, there is a tradeoff between power consumption, coverage area,

and data rate. On the actuation side, having flexibility in designing the irrigation system comes at the cost of demanding high power to operate. Finally, on the data side, there is a tradeoff between the functionalities provided by the data analysis technique, the computation power, and the amount of data demanded.

To this end, although many papers discuss using commercial off-the-shelf software and hardware platforms to provide the needed functionality, none of them performs a technoeconomic analysis. The SF literature lacks an analysis of technology integration's effect on crop yield and returns on investment. In addition, the SF literature should have more discussion on the scalability and robustness of the proposed technologies. This can be done by expanding this work from a theoretical/experimental concept to an applicable industrial model and evaluating its effectiveness.

VI. CONCLUSION

The field of agriculture is heavily shifting toward utilizing technological solutions to enhance agriculture productivity, SF. This article presented a comprehensive survey of the state-of-the-art research performed in the field of SF. To this end, this article identified the most influential technologies affecting farming practices and structures. Analysis of technology integration is presented highlighting their advancements, challenges, and solutions. The discussion in this article provides a better understanding of the essential dimensions of innovative technologies for integrators.

ACKNOWLEDGMENT

REFERENCES

[1] Food and Agriculture Organization of the United Nations. (2017). *The Future of Food and Agriculture—Trends and Challenges*. Accessed: Jun. 22, 2021. [Online]. Available: http://www.fao.org/3/i6583e/i6583e.pdf

[2] Q. T. Minh et al., "A cost-effective smart farming system with knowledge base," in *Proc. 8th Int. Symp. Inf. Commun. Technol.*, Dec. 2017, pp. 309–316.

[3] A. Mittal, S. Sarangi, S. Ramanath, P. V. Bhatt, R. Sharma, and P. Srinivasu, "IoT-based precision monitoring of horticultural crops—A case-study on cabbage and capsicum," in *Proc. IEEE Global Hum. Technol. Conf. (GHTC)*, Oct. 2018, pp. 1–7.

[4] A. T. Balafoutis et al., "Smart farming technologies—Description, taxonomy and economic impact," in *Precision Agriculture: Technology and Economic Perspectives*. New York, NY, USA: Springer, 2017, pp. 21–77.

[5] R. Rayhana, G. Xiao, and Z. Liu, "Internet of Things empowered smart greenhouse farming," *IEEE J. Radio Freq. Identificat.*, vol. 4, no. 3, pp. 195–211, Sep. 2020, doi: 10.1109/JRFID.2020.2984391.

[6] 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. 156237–156271, 2019.

[7] J. Devare and N. Hajare, "A survey on IoT based agricultural crop growth monitoring and quality control," in *Proc. Int. Conf. Commun. Electron. Syst. (ICCES)*, Coimbatore, India, Jul. 2019, pp. 1624–1630.

[8] T. Hidayat, R. Mahardiko, and F. D. Sianturi Tigor, "Method of systematic literature review for Internet of Things in ZigBee smart agriculture," in *Proc. 8th Int. Conf. Inf. Commun. Technol. (ICoICT)*, Yogyakarta, Indonesia, Jun. 2020, pp. 1–4.

[9] J. M. Talavera et al., "Review of IoT applications in agro-industrial and environmental fields," *Comput. Electron. Agricult.*, vol. 142, no. 1, pp. 283–297, 2017.

[10] M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour, and E. M. Aggoune, "Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk," *IEEE Access*, vol. 7, pp. 129551–129583, 2019, doi: 10.1109/ACCESS.2019.2932609.

[11] B. B. Sharma and N. Kumar, "Internet of Things-based hardware and software for smart agriculture: A review," in *Proc. ICRIC*. Cham, Switzerland: Springer, 2020, pp. 151–157, doi: 10.1007/978-3-030-29407-6_13.

[12] N. Johnson, M. B. S. Kumar, and T. Dhannia, "A study on the significance of smart IoT sensors and data science in digital agriculture," in *Proc. Adv. Comput. Commun. Technol. High Perform. Appl. (ACCTHPA)*, Cochin, India, Jul. 2020, pp. 80–88.

[13] R. K. Devi and M. Muthukannan, "An Internet of Things-based economical agricultural integrated system for farmers: A review," in *Proc. 4th Int. Conf. Intell. Comput. Control Syst. (ICICCS)*, Madurai, India, May 2020, pp. 666–673.

[14] S. Solanke, P. Mehare, S. Shinde, V. Ingle, and S. Zope, "IoT based crop disease detection and pesting for Greenhouse—A review," in *Proc. 3rd Int. Conf. Converg. Technol. (I2CT)*, Pune, India, Apr. 2018, pp. 1–4, doi: 10.1109/I2CT.2018.8529156.

[15] D. K. Sreekantha and A. Kavya, "Agricultural crop monitoring using IoT—A study," in *Proc. 11th Int. Conf. Intell. Syst. Control (ISCO)*, Jan. 2017, pp. 134–139.

[16] M. S. Mekala and P. Viswanathan, "A survey: Smart agriculture IoT with cloud computing," in *Proc. Int. Conf. Microelectron. Devices, Circuits Syst. (ICMDCS)*, Vellore, India, Aug. 2017, pp. 1–7.

[17] C. M. D. Morais, D. Sadok, and J. Kelner, "An IoT sensor and scenario survey for data researchers," *J. Brazilian Comput. Soc.*, vol. 25, no. 1, pp. 1–17, Dec. 2019, doi: 10.1186/s13173-019-0085-7.

[18] 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 Things J.*, vol. 5, no. 5, pp. 3758–3773, Oct. 2018.

[19] P. Kanupuru and N. V. U. Reddy, "Suron IoT and its applications in agriculture," in *Proc. Int. Conf. Netw., Embedded Wireless Syst. (ICNEWS)*, Bengaluru, India, Dec. 2018, pp. 1–5.

[20] A. Muniasamy, "Machine learning for smart farming: A focus on desert agriculture," in *Proc. Int. Conf. Comput. Inf. Technol. (ICCIT)*, Tabuk, Saudi Arabia, Sep. 2020, pp. 1–5.

[21] S. Wolfert, L. Ge, C. Verdouw, and M.-J. Bogaardt, "Big data in smart farming—A review," *Agricult. Syst.*, vol. 153, pp. 69–80, May 2017.

[22] A. Kamilaris, A. Kartakoullis, and F. X. Prenafeta-Boldú, "A review on the practice of big data analysis in agriculture," *Comput. Electron. Agricult.*, vol. 143, no. 1, pp. 23–37, 2017.

[23] N. Chergui, M.-T. Kechadi, and M. McDonnell, "The impact of data analytics in digital agriculture: A review," in *Proc. Int. Multi-Conf. Org. Knowl. Adv. Technol. (OCTA)*, Feb. 2020, pp. 1–13.

[24] Y. Gandge and Sandhya, "A study on various data mining techniques for crop yield prediction," in *Proc. Int. Conf. Electr., Electron., Commun., Comput., Optim. Techn. (ICEECCOT)*, Mysuru, India, Dec. 2017, pp. 420–423.

[25] A. Shukla, D. B. Mehta, A. R. Choksi, H. B. Shah, and V. M. Joshi, "Survey of zone tessellation techniques for defined parameters in precision agriculture," in *Proc. Int. Conf. Innov. Inf., Embedded Commun. Syst. (ICIIECS)*, Mar. 2015, pp. 1–5.

[26] E. Rewar, B. P. Singh, and O. P. Sharma, "Evaluation of foliar diseases using image processing," in *Proc. Int. Conf. Current Trends Comput., Electr., Electron. Commun. (CTCEEC)*, Mysore, India, Sep. 2017, pp. 611–615.

[27] A. A. Bharate and M. S. Shirdhonkar, "A review on plant disease detection using image processing," in *Proc. Int. Conf. Intell. Sustain. Syst. (ICISS)*, Palladam, India, Dec. 2017, pp. 103–109.

[28] S. S. Kumar and B. K. Raghavendra, "Diseases detection of various plant leaf using image processing techniques: A review," in *Proc. 5th Int. Conf. Adv. Comput. Commun. Syst. (ICACCS)*, Coimbatore, India, Mar. 2019, pp. 313–316.

[29] M. N. I. Sarker, M. Wu, B. Chanthamith, S. Yusufzada, D. Li, and J. Zhang, "Big data driven smart agriculture: Pathway for sustainable development," in *Proc. 2nd Int. Conf. Artif. Intell. Big Data (ICAIBD)*, Chengdu, China, May 2019, pp. 60–65.

[30] S. Singh, P. Singh, and A. Kaur, "A survey on image processing techniques for seeds classification," in *Proc. 4th Int. Conf. Comput. Sci. (ICCS)*, Jalandhar, India, Aug. 2018, pp. 143–150, doi: 10.1109/ICCS.2018.00032.

[31] D. P. Kuchipudi and T. R. Babu, "A review on segmentation of plant maladies and pathological parts from the leaf images in agriculture crop," in *Proc. 2nd Int. Conf. Intell. Comput., Instrum. Control Technol. (ICICICT)*, vol. 1, Jul. 2019, pp. 927–934.

[32] Seema, A. Kumar, and G. S. Gill, "Automatic fruit grading and classification system using computer vision: A review," in *Proc. 2nd Int. Conf. Adv. Comput. Commun. Eng.*, May 2015, pp. 598–603, doi: 10.1109/ICACCE.2015.15.

[33] P. K. R. Maddikunta et al., "Unmanned aerial vehicles in smart agriculture: Applications, requirements, and challenges," *IEEE Sensors J.*, vol. 21, no. 16, pp. 17608–17619, Aug. 2021, doi: 10.1109/JSEN.2021.3049471.

[34] M. A. Latif, "An agricultural perspective on flying sensors: State of the art, challenges, and future directions," *IEEE Geosci. Remote Sens. Mag.*, vol. 6, no. 4, pp. 10–22, Jul. 2018.

[35] Z. Stamenković, S. Randjić, I. Santamaria, U. Pešović, G. Panić, and S. Tanasković, "Advanced wireless sensor nodes and networks for agricultural applications," in *Proc. 24th Telecommun. Forum (TELFOR)*, Belgrade, Serbia, Nov. 2016, pp. 1–8.

[36] Y. Salima, J. F. M. Peira, G. R. de la Horra, and P. V. M. Ablanque, "Remote sensing data: Useful way for the precision agriculture," in *Proc. 6th Int. Conf. Internet Things, Syst., Manage. Secur. (IOTSMS)*, Granada, Spain, Oct. 2019, pp. 603–609.

[37] T. Ojha, S. Misra, and N. S. Raghuwanshi, "Wireless sensor networks for agriculture: The state-of-the-art in practice and future challenges," *Comput. Electron. Agricult.*, vol. 118, pp. 66–84, Oct. 2015, doi: 10.1016/j.compag.2015.08.011.

[38] U. Garlando, L. Bar-On, A. Avni, Y. Shacham-Diamand, and D. Demarchi, "Plants and environmental sensors for smart agriculture, an overview," in *Proc. IEEE SENSORS*, Rotterdam, The Netherlands, Oct. 2020, pp. 1–4, doi: 10.1109/SENSORS47125.2020.9278748.

[39] H. Nandanwar, A. Chauhan, D. Pahl, and H. Meena, "A survey of application of ML and data mining techniques for smart irrigation system," in *Proc. 2nd Int. Conf. Inventive Res. Comput. Appl. (ICIRCA)*, Coimbatore, India, Jul. 2020, pp. 205–212.

[40] S. Ghosh, S. Sayyed, K. Wani, M. Mhatre, and H. A. Hingoliwala, "Smart irrigation: A smart drip irrigation system using cloud, Android and data mining," in *Proc. IEEE Int. Conf. Adv. Electron., Commun. Comput. Technol. (ICAECCT)*, Pune, India, Dec. 2016, pp. 236–239.

[41] H. I. Tangarife and A. E. Díaz, "Robotic applications in the automation of agricultural production under greenhouse: A review," in *Proc. IEEE 3rd Colombian Conf. Autom. Control (CCAC)*, Cartagena, Colombia, Oct. 2017, pp. 1–6, doi: 10.1109/CCAC.2017.8276478.

[42] S. S. H. Hajjaj and K. S. M. Sahari, "Review of agriculture robotics: Practicality and feasibility," in *Proc. IEEE Int. Symp. Robot. Intell. Sensors (IRIS)*, Tokyo, Japan, Dec. 2016, pp. 194–198.

[43] Y. Wei, W. Li, D. An, D. Li, Y. Jiao, and Q. Wei, "Equipment and intelligent control system in aquaponics: A review," *IEEE Access*, vol. 7, pp. 169306–169326, 2019, doi: 10.1109/ACCESS.2019.2953491.

[44] K. Jha, A. Doshi, P. Patel, and M. Shah, "A comprehensive review on automation in agriculture using artificial intelligence," *Artif. Intell. Agricult.*, vol. 2, pp. 1–12, Jun. 2019.

[45] P. Suebsombut, A. Sekhari, P. Sureephong, and A. Bouras, "Classification and trends in knowledge research relevance and context for smart farm technology development," in *Proc. 11th Int. Conf. Softw., Knowl., Inf. Manag. Appl. (SKIMA)*, Malabe, Sri Lanka, Dec. 2017, pp. 1–7.

[46] D. Pivoto, P. D. Waquil, E. Talamini, C. P. S. Finocchio, V. F. D. Corte, and G. de Vargas Mores, "Scientific development of smart farming technologies and their application in Brazil," *Inf. Process. Agricult.*, vol. 5, no. 1, pp. 21–32, Mar. 2018.

[47] P. Suebsombut, A. Sekhari, P. Sureepong, P. Ueasangkomsate, and A. Bouras, "The using of bibliometric analysis to classify trends and future directions on 'smart farm,'" in *Proc. Int. Conf. Digit. Arts, Media Technol. (ICDAMT)*, Chiang Mai, Thailand, 2017, pp. 136–141, doi: 10.1109/ICDAMT.2017.7904950.

[48] P. Suebsombut, S. Chernbumroong, P. Sureephong, P. Jaroenwanit, P. Phuensane, and A. Sekhari, "Comparison of smart agriculture literacy of farmers in Thailand," in *Proc. Joint Int. Conf. Digit. Arts, Media Technol. ECTI Northern Sect. Conf. Electr., Electron., Comput. Telecommun. Eng. (ECTI DAMT NCON)*, Mar. 2020, pp. 242–245.

[49] N. Alrobah and N. Khan, "Proposing guideline for conclusive use of smart agriculture application in KSA," in *Proc. Int. Conf. Comput. Inf. Technol. (ICCIT)*, Tabuk, Saudi Arabia, Sep. 2020, pp. 1–5.

[50] J. P. T. Higgins, J. Chandler, M. Cumpston, T. Li, M. J. Page, and V. A. Welch, Eds., *Cochrane Handbook for Systematic Reviews of Interventions*. London, U.K.: Cochrane, 2022. [Online]. Available: https://www.training.cochrane.org/handbook

[51] *Journal Citation Reports Science Edition*, Clarivate Anal., London, U.K., 2021.

[52] W. Isaac and A. Na, "On-the-go soil nitrogen sensor based on near infrared spectroscopy," in *Proc. Int. Conf. Inf. Technol. (InCITe) Next Gener. IT Summit Theme Internet Things, Connect Your Worlds*, Noida, India, Oct. 2016, pp. 312–315.

[53] B. H. Shraddha, R. M. Shet, P. Nikita, and N. C. Iyer, "Nutrient detection for maize plant using noninvasive technique," in *Proc. Int. Conf. Adv. Commun. Comput. Technol. (ICACCT)*, Sangamner, India, Feb. 2018, pp. 504–509.

[54] B. O'Flynn, M. De Donno, C. Barrett, C. Robinson, and A. O. Riordan, "Smart microneedle sensing systems for security in agriculture, food and the environment (SAFE)," in *Proc. IEEE SENSORS*, Glasgow, U.K., Oct./Nov. 2017, pp. 1–3, doi: 10.1109/ICSENS.2017.8233884.

[55] J. Baek and M. W. Kanampiu, "A strategic sensor placement for a smart farm water sprinkler system: A computational model," in *Proc. 23rd Int. Conf. Adv. Commun. Technol. (ICACT)*, Pyeongchang, South Korea, Feb. 2021, pp. 53–57.

[56] M. Margarat, B. E. Caroline, R. Aathisha, S. Dhanalakshmi, A. Balasoundhariya, and D. Deena, "All optical sensors for IoT applications," in *Proc. Int. Conf. Syst., Comput., Autom. Netw. (ICSCAN)*, Pondicherry, India, Jul. 2020, pp. 1–5.

[57] K. Ishibashi, Y. Oota, K. Suzuki, and R. Takitoge, "Plants growth sensing using beat sensors," in *Proc. IEEE SENSORS*, New Delhi, India, Oct. 2018, pp. 1–4, doi: 10.1109/ICSENS.2018.8589703.

[58] L. Zhu and P.-Y. Chen, "A compact, zero-power and low-noise harmonic-transponder for liquid and moisture sensing," in *Proc. IEEE Int. Symp. Antennas Propag. USNC-URSI Radio Sci. Meeting*, Atlanta, GA, USA, Jul. 2019, pp. 1109–1110.

[59] T. Athauda, P. C. Banerjee, and N. C. Karmakar, "Microwave characterization of chitosan hydrogel and its use as a wireless pH sensor in smart packaging applications," *IEEE Sensors J.*, vol. 20, no. 16, pp. 8990–8996, Aug. 2020.

[60] R. Elfrink, M. Burghoorn, M. Zevenbergen, R. van Hal, and H. Schoo, "Integrated climate and water sensors for greenhouses," in *Proc. Smart Syst. Integr., 13th Int. Conf. Exhib. Integr. Issues Miniaturized Syst.* Barcelona, Spain: VDE, 2019, pp. 1–8.

[61] A. K. R. Segundo, E. S. Pinto, P. M. de Barros Monteiro, and J. H. Martins, "Sensor for measuring electrical parameters of soil based on auto-balancing bridge circuit," in *Proc. IEEE SENSORS*, Glasgow, U.K., Oct. 2017, pp. 1–3, doi: 10.1109/ICSENS.2017.8234001.

[62] Z. Zheng, Y. Tao, Y. Chen, F. Zhu, and D. Chen, "An efficient preference-based sensor selection method in Internet of Things," *IEEE Access*, vol. 7, pp. 168536–168547, 2019.

[63] M. V. Suhas, S. Tejas, Snigdha, S. Yaji, and S. Salvi, "AgrOne: An agricultural drone using Internet of Things, data analytics and cloud computing features," in *Proc. 4th Int. Conf. for Converg. Technol. (I2CT)*, Mangaluru, India, Oct. 2018, pp. 1–5.

[64] S. Namani and B. Gonen, "Smart agriculture based on IoT and cloud computing," in *Proc. 3rd Int. Conf. Inf. Comput. Technol. (ICICT)*, San Jose, CA, USA, Mar. 2020, pp. 553–556.

[65] I. A. Sulistijono, M. R. Ramadhani, and A. Risnumawan, "Aerial drone mapping and trajectories generator for agricultural ground robots," in *Proc. Int. Symp. Community-Centric Syst. (CcS)*, Tokyo, Japan, Sep. 2020, pp. 1–6.

[66] K. Priandana, M. Hazim, Wulandari, and B. Kusumoputro, "Development of autonomous UAV quadcopters using pixhawk controller and its flight data acquisition," in *Proc. Int. Conf. Comput. Sci. Appl. Agricult. (ICOSICA)*, Bogor, Indonesia, Sep. 2020, pp. 1–6, doi: 10.1109/ICOSICA49951.2020.9243289.

[67] D. Popescu, F. Stoican, L. Ichim, G. Stamatescu, and C. Dragana, "Collaborative UAV-WSN system for data acquisition and processing in agriculture," in *Proc. 10th IEEE Int. Conf. Intell. Data Acquisition Adv. Comput. Syst., Technol. Appl. (IDAACS)*, vol. 1, Metz, France, Sep. 2019, pp. 519–524.

[68] R. Galati, G. Reina, A. Messina, and A. Gentile, "Survey and navigation in agricultural environments using robotic technologies," in *Proc. 14th IEEE Int. Conf. Adv. Video Signal Based Surveill. (AVSS)*, Lecce, Italy, Aug. 2017, pp. 1–6.

[69] A. Nagchaudhuri, M. Mitra, C. Hartman, T. Ford, and J. Pandya, "Mobile robotic platforms to support smart farming efforts at UMES," in *Proc. 14th IEEE/ASME Int. Conf. Mech. Embedded Syst. Appl. (MESA)*, Oulu, Finland, Jul. 2018, pp. 1–7.

[70] M. F. S. Xaud, A. C. Leite, and P. J. From, "Thermal image based navigation system for skid-steering mobile robots in sugarcane crops," in *Proc. Int. Conf. Robot. Autom. (ICRA)*, Montreal, QC, Canada, May 2019, pp. 1808–1814.

[71] A. Habib, W. Xiong, F. He, H. L. Yang, and M. Crawford, "Improving orthorectification of UAV-based push-broom scanner imagery using derived orthophotos from frame cameras," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 10, no. 1, pp. 262–276, Jan. 2017, doi: 10.1109/JSTARS.2016.2520929.

[72] P. Nintanavongsa and I. Pitimon, "Impact of sensor mobility on UAV-based smart farm communications," in *Proc. Int. Electr. Eng. Congr. (iEECON)*, Pattaya, Thailand, Mar. 2017, pp. 1–4.

[73] P. Nintanavongsa, W. Yaemvachi, and I. Pitimon, "A self-sustaining unmanned aerial vehicle routing protocol for smart farming," in *Proc. Int. Symp. Intell. Signal Process. Commun. Syst. (ISPACS)*, Phuket, Thailand, Oct. 2016, pp. 1–5.

[74] A. Mancini, E. Frontoni, and P. Zingaretti, "Satellite and UAV data for precision agriculture applications," in *Proc. Int. Conf. Unmanned Aircr. Syst. (ICUAS)*, Atlanta, GA, USA, Jun. 2019, pp. 491–497, doi: 10.1109/ICUAS.2019.8797930.

[75] Y. C. Hsieh et al., "Stabilities study of the current agriculture use UAV and future design," in *Proc. IEEE Int. Conf. Appl. Syst. Invention (ICASI)*, Chiba, Japan, Apr. 2018, pp. 746–749.

[76] X.-K. Xu, X.-M. Li, and R.-H. Zhang, "Remote configurable image acquisition lifting robot for smart agriculture," in *Proc. IEEE 4th Adv. Inf. Technol., Electron. Autom. Control Conf. (IAEAC)*, Chengdu, China, Dec. 2019, pp. 1545–1548.

[77] K. L. Krishna, O. Silver, W. F. Malende, and K. Anuradha, "Internet of Things application for implementation of smart agriculture system," in *Proc. Int. Conf. I-SMAC (IoT Social, Mobile, Analytics Cloud) (I-SMAC)*, Palladam, India, Feb. 2017, pp. 54–59.

[78] C. Di Franco and G. Buttazzo, "Energy-aware coverage path planning of UAVs," in *Proc. IEEE Int. Conf. Auto. Robot Syst. Competitions*, Vila Real, Portugal, Apr. 2015, pp. 111–117.

[79] I. G. Ferrão et al., "STUART: Resilient architecture to dynamically manage unmanned aerial vehicle networks under attack," in *Proc. IEEE Symp. Comput. Commun. (ISCC)*, Rennes, France, Jul. 2020, pp. 1–6, doi: 10.1109/ISCC50000.2020.9219689.

[80] J. Zhao, Y. Wang, Z. Fei, and X. Wang, "UAV deployment design for maximizing effective data with delay constraint in a smart farm," in *Proc. IEEE/CIC Int. Conf. Commun. China (ICCC)*, Chongqing, China, Aug. 2020, pp. 424–429.

[81] G. Livanos et al., "Extraction of reflectance maps for smart farming applications using unmanned aerial vehicles," in *Proc. 12th Int. Symp. Commun. Syst., Netw. Digit. Signal Process. (CSNDSP)*, Porto, Portugal, Jul. 2020, pp. 1–6.

[82] R. Moeller, T. Deemyad, and A. Sebastian, "Autonomous navigation of an agricultural robot using RTK GPS and pixhawk," in *Proc. Intermountain Eng., Technol. Comput. (IETC)*, Orem, UT, USA, Oct. 2020, pp. 1–6, doi: 10.1109/IETC47856.2020.9249176.

[83] L. Chaari, S. Chahbani, and J. Rezgui, "Vulnerabilities assessment for unmanned aerial vehicles communication systems," in *Proc. Int. Symp. Netw., Comput. Commun. (ISNCC)*, Montreal, QC, Canada, Oct. 2020, pp. 1–6.

[84] S. Lata and H. K. Verma, "Selection of sensor number and locations in intelligent greenhouse," in *Proc. 3rd Int. Conf. Condition Assessment Techn. Electr. Syst. (CATCON)*, Rupnagar, India, Nov. 2017, pp. 58–62.

[85] S. Maurya and V. K. Jain, "Threshold sensitive region-based hybrid routing protocol for precision agriculture," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Doha, Qatar, Apr. 2016, pp. 169–174.

[86] A. Gupta, H. P. Gupta, P. Kumari, R. Mishra, S. Saraswat, and T. Dutta, "A real-time precision agriculture monitoring system using mobile sink in WSNs," in *Proc. IEEE Int. Conf. Adv. Netw. Telecommun. Syst. (ANTS)*, Indore, India, Dec. 2018, pp. 1–5, doi: 10.1109/ANTS.2018.8710048.

[87] S. Suakanto, V. J. L. Engel, M. Hutagalung, and D. Angela, "Sensor networks data acquisition and task management for decision support of smart farming," in *Proc. Int. Conf. Inf. Technol. Syst. Innov. (ICITSI)*, Bandung, Indonesia, Oct. 2016, pp. 1–5, doi: 10.1109/ICITSI.2016.7858233.

[88] D. Andritoiu, L.-C. Bazavan, F.-L. Besnea, H. Roibu, and N.-G. Bizdoaca, "Agriculture autonomous monitoring and decisional mechatronic system," in *Proc. 19th Int. Carpathian Control Conf. (ICCC)*, May 2018, pp. 241–246.

[89] M. AshifuddinMondal and Z. Rehena, "IoT based intelligent agriculture field monitoring system," in *Proc. 8th Int. Conf. Cloud Comput., Data Sci. Eng. (Confluence)*, Noida, India, Jan. 2018, pp. 625–629, doi: 10.1109/CONFLUENCE.2018.8442535.

[90] M. K. Saini and R. K. Saini, "Agriculture monitoring and prediction using Internet of Things (IoT)," in *Proc. 6th Int. Conf. Parallel, Distrib. Grid Comput. (PDGC)*, Waknaghat, India, Nov. 2020, pp. 53–56, doi: 10.1109/PDGC50313.2020.9315836.

[91] H. Andrianto, Suhardi, and A. Faizal, "Development of smart greenhouse system for hydroponic agriculture," in *Proc. Int. Conf. Inf. Technol. Syst. Innov. (ICITSI)*, Bandung, Indonesia, Oct. 2020, pp. 335–340.

[92] M. Shrihari, "A smart wireless system to automate production of crops and stop intrusion using deep learning," in *Proc. 3rd Int. Conf. Smart Syst. Inventive Technol. (ICSSIT)*, Tirunelveli, India, Aug. 2020, pp. 1038–1045.

[93] A. J. Rau, J. Sankar, A. R. Mohan, D. D. Krishna, and J. Mathew, "IoT based smart irrigation system and nutrient detection with disease analysis," in *Proc. IEEE Region 10 Symp. (TENSYMP)*, Jul. 2017, pp. 1–4.

[94] Z. Muhammad, M. A. A. M. Hafez, N. A. M. Leh, Z. M. Yusoff, and S. A. Hamid, "Smart agriculture using Internet of Things with raspberry pi," in *Proc. 10th IEEE Int. Conf. Control Syst., Comput. Eng. (ICCSCE)*, Penang, Malaysia, Aug. 2020, pp. 85–90.

[95] J. Granda-Cantuna, C. Molina-Colcha, S.-E. Hidalgo-Lupera, and C.-D. Valarezo-Varela, "Design and implementation of a wireless sensor network for precision agriculture operating in API mode," in *Proc. Int. Conf. eDemocracy eGovernment (ICEDEG)*, Ambato, Ecuador, Apr. 2018, pp. 144–149.

[96] V. P. Prabha, S. M. Sarala, and C. S. Sharmila, "Robust smart irrigation system using hydroponic farming based on data science and IoT," in *Proc. IEEE Bengaluru Hum. Technol. Conf. (B-HTC)*, Oct. 2020, pp. 1–4.

[97] C. Changqing, L. Hui, and H. Wenjun, "Internet of agriculture-based low cost smart greenhouse remote monitor system," in *Proc. Chin. Autom. Congr. (CAC)*, Xi'an, China, Nov. 2018, pp. 3940–3945.

[98] A. E. Ruano et al., "A neural-network based intelligent weather station," in *Proc. IEEE 9th Int. Symp. Intell. Signal Process. (WISP)*, Siena, Italy, May 2015, pp. 1–6.

[99] F. Pitu and N. C. Gaitan, "Surveillance of SigFox technology integrated with environmental monitoring," in *Proc. Int. Conf. Develop. Appl. Syst. (DAS)*, May 2020, pp. 69–72.

[100] R. Varghese and S. Sharma, "Affordable smart farming using IoT and machine learning," in *Proc. 2nd Int. Conf. Intell. Comput. Control Syst. (ICICCS)*, Madurai, India, Jun. 2018, pp. 645–650, doi: 10.1109/ICCONS.2018.8663044.

[101] F. B. Poyen, A. Ghosh, P. Kundu, S. Hazra, and N. Sengupta, "Prototype model design of automatic irrigation controller," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–17, 2021, doi: 10.1109/TIM.2020.3031760.

[102] J. J. Estrada-López, A. A. Castillo-Atoche, J. Vázquez-Castillo, and E. Sánchez-Sinencio, "Smart soil parameters estimation system using an autonomous wireless sensor network with dynamic power management strategy," *IEEE Sensors J.*, vol. 18, no. 21, pp. 8913–8923, Nov. 2018.

[103] E. Avşar, K. Buluş, M. A. Saridaş, and B. Kapur, "Development of a cloud-based automatic irrigation system: A case study on strawberry cultivation," in *Proc. 7th Int. Conf. Modern Circuits Syst. Technol. (MOCAST)*, May 2018, pp. 1–4.

[104] D. Xue and W. Huang, "Smart agriculture wireless sensor routing protocol and node location algorithm based on Internet of Things technology," *IEEE Sensors J.*, vol. 21, no. 22, pp. 24967–24973, Nov. 2021.

[105] F. B. Culibrina and E. P. Dadios, "Smart farm using wireless sensor network for data acquisition and power control distribution," in *Proc. Int. Conf. Humanoid, Nanotechnol., Inf. Technol., Commun. Control, Environ. Manage. (HNICEM)*, Cebu, Philippines, Dec. 2015, pp. 1–6.

[106] Q. Wu, Y. Liang, Y. Li, and Y. Liang, "Research on intelligent acquisition of smart agricultural big data," in *Proc. 25th Int. Conf. Geoinform.*, Buffalo, NY, USA, Aug. 2017, pp. 1–7.

[107] S. Rottmann, B. Gernert, J. Käberich, U. Kulau, and L. Wolf, "AWuR: An adaptive routing protocol for energy efficient two-platform nodes in wireless DTNs," in *Proc. IEEE 14th Int. Conf. Mobile Ad Hoc Sensor Syst. (MASS)*, Orlando, FL, USA, Oct. 2017, pp. 293–297, doi: 10.1109/MASS.2017.51.

[108] T. M. Behera, M. S. Khan, S. K. Mohapatra, U. C. Samail, and M. Z. A. Bhuiyan, "Energy-efficient routing for greenhouse monitoring using heterogeneous sensor networks," in *Proc. Int. Conf. Internet Things (iThings) IEEE Green Comput. Commun. (GreenCom) IEEE Cyber, Phys. Social Comput. (CPSCom) IEEE Smart Data (Smart-Data)*, Atlanta, GA, USA, Jul. 2019, pp. 953–958.

[109] V. Romanov, I. Galelyuka, H. Antonova, O. Kovyrova, V. Hrusha, and O. Voronenko, "Application of wireless sensor networks for digital agriculture," in *Proc. 10th IEEE Int. Conf. Intell. Data Acquisition Adv. Comput. Syst., Technol. Appl. (IDAACS)*, Metz, France, Sep. 2019, pp. 340–344.

[110] Z. Hu et al., "Application of non-orthogonal multiple access in wireless sensor networks for smart agriculture," *IEEE Access*, vol. 7, pp. 87582–87592, 2019, doi: 10.1109/ACCESS.2019.2924917.

[111] J. W. Kimball, B. T. Kuhn, and R. S. Balog, "A system design approach for unattended solar energy harvesting supply," *IEEE Trans. Power Electron.*, vol. 24, no. 4, pp. 952–962, Apr. 2009.

[112] M. Bodić, P. Vuković, V. Rajs, M. Vasiljević-Toskić, and J. Bajić, "Station for soil humidity, temperature and air humidity measurement with SMS forwarding of measured data," in *Proc. 41st Int. Spring Seminar Electron. Technol. (ISSE)*, Zlatibor, Serbia, May 2018, pp. 1–5, doi: 10.1109/ISSE.2018.8443618.

[113] M. E. Bayrakdar, "A smart insect pest detection technique with qualified underground wireless sensor nodes for precision agriculture," *IEEE Sensors J.*, vol. 19, no. 22, pp. 10892–10897, Nov. 2019.

[114] N. Sumathi and B. Venkatalakshmi, "Design of 433 MHz compatible matching network of wake-up receiver for wireless sensor node," in *Proc. Global Conf. Commun. Technol. (GCCT)*, Thuckalay, India, Apr. 2015, pp. 807–811.

[115] M. Boulou, T. Yelemou, D. A. Rollande, and H. Tall, "DEARP: Dynamic energy aware routing protocol for wireless sensor network," in *Proc. IEEE 2nd Int. Conf. Smart Cities Commun. (SCCIC)*, Ouagadougou, Burkina Faso, Dec. 2020, pp. 1–6.

[116] O. Gulec, E. Haytaoglu, and S. Tokat, "A novel distributed CDS algorithm for extending lifetime of WSNs with solar energy harvester nodes for smart agriculture applications," *IEEE Access*, vol. 8, pp. 58859–58873, 2020, doi: 10.1109/ACCESS.2020.2983112.

[117] B. Chatterjee et al., "Context-aware collaborative intelligence with spatio-temporal in-sensor-analytics for efficient communication in a large-area IoT testbed," *IEEE Internet Things J.*, vol. 8, no. 8, pp. 6800–6814, Apr. 2021, doi: 10.1109/JIOT.2020.3036087.

[118] J. Gialelis, G. Theodorou, M. Fokaeos, and D. Karadimas, "An integrated low cost IoT node based on discrete components for customized smart applications; use case on precision agriculture," in *Proc. 8th Medit. Conf. Embedded Comput. (MECO)*, Budva, Montenegro, Jun. 2019, pp. 1–4.

[119] S. Srisruthi, N. Swarna, G. M. S. Ros, and E. Elizabeth, "Sustainable agriculture using eco-friendly and energy efficient sensor technology," in *Proc. IEEE Int. Conf. Recent Trends Electron., Inf. Commun. Technol. (RTEICT)*, May 2016, pp. 1442–1446.

[120] A. M. Jawad, H. M. Jawad, R. Nordin, S. K. Gharghan, N. F. Abdullah, and M. J. Abu-Alshaeer, "Wireless power transfer with magnetic resonator coupling and sleep/active strategy for a drone charging station in smart agriculture," *IEEE Access*, vol. 7, pp. 139839–139851, 2019, doi: 10.1109/ACCESS.2019.2943120.

[121] C.-C. Liu, S.-A. Yang, T.-H. Cheng, and S.-Y. Chen, "Embedded antenna design based on zero and pole resonances for wireless sensor modules for applications in advanced greenhouses," in *Proc. IEEE Int. Symp. Radio-Frequency Integr. Technol. (RFIT)*, Aug. 2015, pp. 205–207.

[122] S. Sadowski and P. Spachos, "Solar-powered smart agricultural monitoring system using Internet of Things devices," in *Proc. IEEE 9th Annu. Inf. Technol., Electron. Mobile Commun. Conf. (IEMCON)*, Vancouver, BC, Canada, Nov. 2018, pp. 18–23.

[123] K. A. Patil and N. R. Kale, "A model for smart agriculture using IoT," in *Proc. Int. Conf. Global Trends Signal Process., Inf. Comput. Commun. (ICGTSPICC)*, Jalgaon, India, Dec. 2016, pp. 543–545, doi: 10.1109/ICGTSPICC.2016.7955360.

[124] R. G. Baldovino, I. C. Valenzuela, and E. P. Dadios, "Implementation of a low-power wireless sensor network for smart farm applications," in *Proc. IEEE 10th Int. Conf. Human., Nanotechnol., Inf. Technol., Commun. Control, Environ. Manag. (HNICEM)*, Baguio City, Philippines, Nov. 2018, pp. 1–5, doi: 10.1109/HNICEM.2018.8666262.

[125] W. Lu et al., "Energy efficiency optimization in SWIPT enabled WSNs for smart agriculture," *IEEE Trans. Ind. Informat.*, vol. 17, no. 6, pp. 4335–4344, Jun. 2021.

[126] U. Kulau, S. Rottmann, S. Schildt, J. van Balen, and L. Wolf, "Undervolting in real world WSN applications: A long-term study," in *Proc. Int. Conf. Distrib. Comput. Sensor Syst. (DCOSS)*, Washington, DC, USA, May 2016, pp. 9–16.

[127] C.-T. Wang, Z. Wang, Y. Zhu, and Z.-H. Han, "The application of data-level fusion algorithm based on adaptive-weighted and support degree in intelligent household greenhouse," in *Innovative Techniques and Applications of Modelling, Identification and Control*, vol. 467. Singapore: Springer, 2018, pp. 93–108.

[128] X. Chen, "Research on data interpolation model with missing data for intelligent greenhouse control," in *Proc. Int. Conf. Robots Intell. Syst. (ICRIS)*, Jun. 2019, pp. 43–45.

[129] N. Fahmi, S. Huda, E. Prayitno, M. U. H. A. Rasyid, M. C. Roziqin, and M. U. Pamenang, "A prototype of monitoring precision agriculture system based on WSN," in *Proc. Int. Seminar Intell. Technol. Appl. (ISITIA)*, Surabaya, Indonesia, Aug. 2017, pp. 323–328, doi: 10.1109/ISITIA.2017.8124103.

[130] L. Dan, W. Hongli, Z. Mengya, and X. Jianqiu, "Intelligent agriculture greenhouse environment monitoring system based on the Android platform," in *Proc. Int. Conf. Smart Grid Electr. Autom. (ICSGEA)*, Changsha, China, May 2017, pp. 358–361.

[131] M. R. M. Kassim, A. N. Harun, I. M. Yusoff, I. Mat, C. P. Kuen, and N. Rahmad, "Applications of wireless sensor networks in shiitake mushroom cultivation," in *Proc. 11th Int. Conf. Sens. Technol. (ICST)*, Sydney, NSW, Australia, Dec. 2017, pp. 1–6.

[132] G. Sahitya, N. Balaji, and C. D. Naidu, "Wireless sensor network for smart agriculture," in *Proc. 2nd Int. Conf. Appl. Theor. Comput. Commun. Technol. (iCATccT)*, Bengaluru, India, 2016, pp. 488–493.

[133] M. K. Gayatri, J. Jayasakthi, and G. S. A. Mala, "Providing smart agricultural solutions to farmers for better yielding using IoT," in *Proc. IEEE Technol. Innov. ICT Agricult. Rural Develop. (TIAR)*, Chennai, India, Jul. 2015, pp. 40–43.

[134] T. Thaher and I. Ishaq, "Cloud-based Internet of Things approach for smart irrigation system: Design and implementation," in *Proc. Int. Conf. Promising Electron. Technol. (ICPET)*, Jerusalem, Israel, Dec. 2020, pp. 32–37.

[135] M. Zhou, Y. Bie, Q. Wang, and Z. Zou, "Design and testing of a monitoring system for mushroom planting greenhouse," in *Proc. IEEE 4th Inf. Technol. Mechatronics Eng. Conf. (ITOEC)*, Chongqing, China, Dec. 2018, pp. 1658–1661.

[136] N. Mahfuz, R. Jahan, M. M. Islam, M. Nigar, and S. Karmokar, "Microcontroller based intelligent greenhouse environment monitoring and controlling system," in *Proc. IEEE Int. Women Eng. (WIE) Conf. Electr. Comput. Eng. (WIECON-ECE)*, Bhubaneswar, India, Dec. 2020, pp. 418–421.

[137] S. Salvi et al., "Cloud based data analysis and monitoring of smart multi-level irrigation system using IoT," in *Proc. Int. Conf. I-SMAC (IoT Social, Mobile, Analytics Cloud) (I-SMAC)*, Feb. 2017, pp. 752–757.

[138] Y. E. M. Hamouda and B. H. Y. Elhabil, "Precision agriculture for greenhouses using a wireless sensor network," in *Proc. Palestinian Int. Conf. Inf. Commun. Technol. (PICICT)*, Gaza, Palestine, May 2017, pp. 78–83.

[139] A. Sengupta, B. Debnath, A. Das, and D. De, "FarmFox: A quad-sensor-based IoT box for precision agriculture," *IEEE Consum. Electron. Mag.*, vol. 10, no. 4, pp. 63–68, Jul. 2021.

[140] R. K. Patil and S. S. Patil, "Cognitive intelligence of Internet of Things in smart agriculture applications," in *Proc. IEEE Pune Sect. Int. Conf. (PuneCon)*, Pune, India, Dec. 2020, pp. 129–132.

[141] T. N. Balasooriya, P. Mantri, and P. Suriyampola, "IoT-based smart watering system towards improving the efficiency of agricultural irrigation," in *Proc. IEEE Global Conf. Artif. Intell. Internet Things (GCAIoT)*, Dubai, United Arab Emirates, Dec. 2020, pp. 1–7.

[142] D. Amu, A. Amuthan, S. S. Gayathri, and A. Jayalakshmi, "Automated irrigation using Arduino sensor based on IoT," in *Proc. Int. Conf. Comput. Commun. Informat. (ICCCI)*, Coimbatore, India, Jan. 2019, pp. 1–6.

[143] S. N. Daskalakis, G. Goussetis, S. D. Assimonis, M. M. Tentzeris, and A. Georgiadis, "A uW backscatter-morse-leaf sensor for low-power agricultural wireless sensor networks," *IEEE Sensors J.*, vol. 18, no. 19, pp. 7889–7898, Oct. 2018, doi: 10.1109/JSEN.2018.2861431.

[144] G. Manogaran, C.-H. Hsu, B. S. Rawal, B. Muthu, C. X. Mavromoustakis, and G. Mastorakis, "ISOF: Information scheduling and optimization framework for improving the performance of agriculture systems aided by industry 4.0," *IEEE Internet Things J.*, vol. 8, no. 5, pp. 3120–3129, Mar. 2021, doi: 10.1109/JIOT.2020.3045479.

[145] S. N. Daskalakis, S. D. Assimonis, G. Goussetis, M. M. Tentzeris, and A. Georgiadis, "The future of backscatter in precision agriculture," in *Proc. IEEE Int. Symp. Antennas Propag. USNC-URSI Radio Sci. Meeting*, Atlanta, GA, USA, Jul. 2019, pp. 647–648, doi: 10.1109/APUSNCURSINRSM.2019.8889330.

[146] S.-N. Daskalakis, J. Kimionis, A. Collado, M. M. Tentzeris, and A. Georgiadis, "Ambient FM backscattering for smart agricultural monitoring," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Jun. 2017, pp. 1339–1341.

[147] D. Davcev, K. Mitreski, S. Trajkovic, V. Nikolovski, and N. Koteli, "IoT agriculture system based on LoRaWAN," in *Proc. 14th IEEE Int. Workshop Factory Commun. Syst. (WFCS)*, Imperia, Italy, Jun. 2018, pp. 1–4, doi: 10.1109/WFCS.2018.8402368.

[148] T. S. Mohammed, O. F. Khan, and A. Al-Bazi, "A novel algorithm based on LoRa technology for open-field and protected agriculture smart irrigation system," in *Proc. 2nd IEEE Middle East North Afr. Commun. Conf. (MENACOMM)*, Manama, Bahrain, Nov. 2019, pp. 1–6, doi: 10.1109/MENACOMM46666.2019.8988583.

[149] H. W. Yoon, D. J. Kim, M. Lee, C. Weon, and A. Smith, "L & M farm: A smart farm based on LoRa & MQTT," in *Proc. Int. Conf. Omni-Layer Intell. Syst. (COINS)*, Barcelona, Spain, Aug. 2020, pp. 1–6, doi: 10.1109/COINS49042.2020.9191387.

[150] R. K. Kodali, M. S. Kuthada, and Y. K. Y. Borra, "LoRa based smart irrigation system," in *Proc. 4th Int. Conf. Comput. Commun. Autom. (ICCCA)*, Greater Noida, India, Dec. 2018, pp. 1–5, doi: 10.1109/CCAA.2018.8777583.

[151] Y.-W. Ma and J.-L. Chen, "Toward intelligent agriculture service platform with LoRa-based wireless sensor network," in *Proc. IEEE Int. Conf. Appl. Syst. Invention (ICASI)*, Chiba, Japan, Apr. 2018, pp. 204–207, doi: 10.1109/ICASI.2018.8394568.

[152] B. Queté et al., "Understanding the tradeoffs of LoRaWAN for IoT-based smart irrigation," in *Proc. IEEE Int. Workshop Metrol. Agricult. Forestry (MetroAgriFor)*, Trento, Italy, Nov. 2020, pp. 73–77, doi: 10.1109/MetroAgriFor50201.2020.9277566.

[153] R. K. Kodali, S. Yerroju, and S. Sahu, "Smart farm monitoring using LoRa enabled IoT," in *Proc. 2nd Int. Conf. Green Comput. Internet Things (ICGCIoT)*, Bengaluru, India Aug. 2018, pp. 391–394, doi: 10.1109/ICGCIoT.2018.8753086.

[154] Y. Yang, "Design and application of intelligent agriculture service system with LoRa-based on wireless sensor network," in *Proc. Int. Conf. Comput. Eng. Appl. (ICCEA)*, Guangzhou, China, Mar. 2020, pp. 712–716.

[155] T. N. Gia, L. Qingqing, J. P. Queralta, Z. Zou, H. Tenhunen, and T. Westerlund, "Edge AI in smart farming IoT: CNNs at the edge and fog computing with LoRa," in *Proc. IEEE AFRICON*, Sep. 2019, pp. 1–6.

[156] Y. S. Chang, Y. H. Chen, and S. K. Zhou, "A smart lighting system for greenhouses based on narrowband-IoT communication," in *Proc. 13th Int. Microsyst., Packag., Assem. Circuits Technol. Conf. (IMPACT)*, Taiwan, Oct. 2018, pp. 275–278.

[157] G. Valecce, P. Petruzzi, S. Strazzella, and L. A. Grieco, "NB-IoT for smart agriculture: Experiments from the field," in *Proc. 7th Int. Conf. Control, Decis. Inf. Technol. (CoDIT)*, Prague, Czech Republic, Jun. 2020, pp. 71–75, doi: 10.1109/CoDIT49905.2020.9263860.

[158] J. D. Adriano, Y. C. T. Mendes, G. A. B. Marcondes, V. Furtado, and J. J. P. C. Rodrigues, "An IoT sensor mote for precision agriculture with several MAC layer protocols support," in *Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC)*, Oct. 2018, pp. 684–688.

[159] J. Dai and M. Sugano, "Low-cost sensor network for collecting real-time data for agriculture by combining energy harvesting and LPWA technology," in *Proc. IEEE Global Hum. Technol. Conf. (GHTC)*, Oct. 2019, pp. 1–4.

[160] H. Lee et al., "Feasibility of networking technology for smart farm: LoRa vs APRS," in *Proc. Int. Conf. Omni-Layer Intell. Syst. (COINS)*, Barcelona, Spain, Aug. 2020, pp. 1–6.

[161] L. Jing and Y. Wei, "Intelligent agriculture system based on LoRa and Qt technology," in *Proc. Chin. Control Decis. Conf. (CCDC)*, Nanchang, China, Jun. 2019, pp. 4755–4760.

[162] G.-J. Horng, M.-X. Liu, and C.-C. Chen, "The smart image recognition mechanism for crop harvesting system in intelligent agriculture," *IEEE Sensors J.*, vol. 20, no. 5, pp. 2766–2781, 2019.

[163] A. Risheh, A. Jalili, and E. Nazerfard, "Smart irrigation IoT solution using transfer learning for neural networks," in *Proc. 10th Int. Conf. Comput. Knowl. Eng. (ICCKE)*, Mashhad, Iran, Oct. 2020, pp. 342–349.

[164] A. Sofwan, S. Sumardi, A. I. Ahmada, I. Ibrahim, K. Budiraharjo, and K. Karno, "Smart greetthings: Smart greenhouse based on Internet of Things for environmental engineering," in *Proc. Int. Conf. Smart Technol. Appl. (ICoSTA)*, Surabaya, Indonesia, Feb. 2020, pp. 1–5.

[165] S. Xue, R. K. Lomotey, and R. Deters, "Enabling sensor data exchanges in unstable mobile architectures," in *Proc. IEEE Int. Conf. Mobile Services*, New York, NY, USA, Jun. 2015, pp. 391–398, doi: 10.1109/MobServ.2015.60.

[166] M. L. Liya and D. Arjun, "A survey of LPWAN technology in agricultural field," in *Proc. 4th Int. Conf. I-SMAC (IoT Social, Mobile, Analytics Cloud) (I-SMAC)*, Oct. 2020, pp. 313–317.

[167] D. K. Singh and R. Sobti, "Wireless communication technologies for Internet of Things and precision agriculture: A review," in *Proc. 6th Int. Conf. Signal Process., Comput. Control (ISPCC)*, Oct. 2021, pp. 765–769.

[168] S. Popli, R. K. Jha, and S. Jain, "A survey on energy efficient narrowband Internet of Things (NBIoT): Architecture, application and challenges," *IEEE Access*, vol. 7, pp. 16739–16776, 2018.

[169] K. E. Khujamatov and T. K. Toshtemirov, "Wireless sensor networks based agriculture 4.0: Challenges and apportions," in *Proc. Int. Conf. Inf. Sci. Commun. Technol. (ICISCT)*, Tashkent, Uzbekistan, Nov. 2020, pp. 1–5.

[170] B. V. Aishwarya, G. Archana, and C. Umayal, "Agriculture robotic vehicle based pesticide sprayer with efficiency optimization," in *Proc. IEEE Technol. Innov. ICT Agricult. Rural Develop. (TIAR)*, Jul. 2015, pp. 59–65, doi: 10.1109/TIAR.2015.7358532.

[171] S. Chen, X. Li, C. Liu, X. Yang, A. Xu, and C. Chen, "Design of intelligent greenhouse planting management robot," in *Proc. Int. Conf. Virtual Reality Intell. Syst. (ICVRIS)*, Sep. 2019, pp. 350–353.

[172] Chethak, A. Kumar, Deepika, S. Santhosh, and R. D'souza, "Feeder Weeder for autonomous farming," in *Proc. 3rd IEEE Int. Conf. Recent Trends Electron., Inf. Commun. Technol. (RTEICT)*, May 2018, pp. 2574–2578.

[173] G. H. do Nascimento, F. Weber, G. Almeida, F. Terra, and P. L. J. Drews, "A perception system for an autonomous pesticide boom sprayer," in *Proc. Latin Amer. Robot. Symp. (LARS), Brazilian Symp. Robot. (SBR) Workshop Robot. Educ. (WRE)*, Oct. 2019, pp. 86–91.

[174] S. Agarwal and N. Agarwal, "An algorithm based low cost automated system for irrigation with soil moisture sensor," in *Proc. Int. Conf. Comput. Commun. Informat. (ICCCI)*, Jan. 2017, pp. 1–5.

[175] S. Meivel, K. Dinakaran, N. Gandhiraj, and M. Srinivasan, "Remote sensing for UREA spraying agricultural (UAV) system," in *Proc. 3rd Int. Conf. Adv. Comput. Commun. Syst. (ICACCS)*, Jan. 2016, pp. 1–6.

[176] S. Maheswaran, S. Sathesh, G. Saran, and B. Vivek, "Automated coconut tree climber," in *Proc. Int. Conf. Intell. Comput. Control (I2C2)*, Jun. 2017, pp. 1–6.

[177] H. Xiaomei, L. Shunke, and C. Jianfei, "Design of agaricus bisporus smart farm," in *Proc. IEEE 4th Int. Conf. Image, Vis. Comput. (ICIVC)*, Jul. 2019, pp. 351–355.

[178] M. A. Litvinov, M. N. Moskovskiy, and I. G. Smirnov, "Automatic system of intelligent seed rate control for selection seeders," in *Proc. IEEE East-West Design Test Symp. (EWDTS)*, Sep. 2018, pp. 1–5.

[179] B. Ragavi, L. Pavithra, P. Sandhiyadevi, G. K. Mohanapriya, and S. Harikirubha, "Smart agriculture with AI sensor by using agrobot," in *Proc. 4th Int. Conf. Comput. Methodol. Commun. (ICCMC)*, Mar. 2020, pp. 1–4.

[180] K. S. Santhosh, M. Anusha, M. Junaid, K. Anju, and Meghana, "IoT based agriculture using AGRIBOT," in *Proc. 4th Int. Conf. Recent Trends Electron., Inf., Commun. Technol. (RTEICT)*, May 2019, pp. 1520–1526.

[181] D. N. Vinod and T. Singh, "Autonomous agricultural farming robot in closed field," in *Proc. 3rd IEEE Int. Conf. Recent Trends Electron., Inf. Commun. Technol. (RTEICT)*, May 2018, pp. 1–7.

[182] D. N. Vinod and T. Singh, "Autonomous farming and surveillance agribot in adjacent boundary," in *Proc. 9th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, Jul. 2018, pp. 1–7, doi: 10.1109/ICCCNT.2018.8494137.

[183] M. Hasan, K. N. W. Uddin, A. Sayeed, and T. Tasneem, "Smart agriculture robotic system based on Internet of Things to boost crop production," in *Proc. 2nd Int. Conf. Robot., Electr. Signal Process. Techn. (ICREST)*, Jan. 2021, pp. 157–162.

[184] G. Kanter, J. Vain, S. Srinivasan, and S. Ramaswamy, "Provably correct configuration management of precision feeding in agriculture4.0," in *Proc. IEEE Int. Conf. Syst., Man Cybern. (SMC)*, Oct. 2019, pp. 1631–1636, doi: 10.1109/SMC.2019.8914057.

[185] C. Schuetz, J. Baur, J. Pfaff, T. Buschmann, and H. Ulbrich, "Evaluation of a direct optimization method for trajectory planning of a 9-DOF redundant fruit-picking manipulator," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2015, pp. 2660–2666.

[186] N. P. D. A. Martini, N. Tamami, and A. H. Alasiry, "Design and development of automatic plant robots with scheduling system," in *Proc. Int. Electron. Symp. (IES)*, Sep. 2020, pp. 302–307.

[187] C. Li et al., "Inverse kinematics study for intelligent agriculture robot development via differential evolution algorithm," in *Proc. Int. Conf. Comput., Control Robot. (ICCCR)*, Jan. 2021, pp. 37–41, doi: 10.1109/ICCCR49711.2021.9349277.

[188] B. Tallapragada and V. Ganugapati, "IoT based intelligent micro irrigation grid with a farmer alert system," in *Proc. Int. Conf. Circuits Syst. Digit. Enterprise Technol. (ICCSDET)*, 2018, pp. 1–7, doi: 10.1109/ICCSDET.2018.8821130.

[189] A. Z. M. T. Kabir, A. M. Mizan, N. Debnath, A. J. Ta-Sin, N. Zinnurayen, and M. T. Haider, "IoT based low cost smart indoor farming management system using an assistant robot and mobile app," in *Proc. 10th Electr. Power, Electron., Commun., Controls Informat. Seminar (EECCIS)*, Malang, Indonesia, Aug. 2020, pp. 155–158.

[190] S. Eiffert, N. D. Wallace, H. Kong, N. Pirmarzdashti, and S. Sukkarieh, "A hierarchical framework for long-term and robust deployment of field ground robots in large-scale farming," in *Proc. IEEE 16th Int. Conf. Autom. Sci. Eng. (CASE)*, Aug. 2020, pp. 948–954.

[191] K. K. Namala, A. V. K. K. Prabhu, A. Math, A. Kumari, and S. Kulkarni, "Smart irrigation with embedded system," in *Proc. IEEE Bombay Sect. Symp. (IBSS)*, Dec. 2016, pp. 1–5.

[192] M. Duan, M. Li, and Y. Xu, "Design and implementation of intelligent irrigation system based on single chip microcomputer," in *Proc. IEEE Int. Conf. Power, Intell. Comput. Syst. (ICPICS)*, Jul. 2019, pp. 653–656.

[193] R. Zaier, S. Zekri, H. Jayasuriya, A. Teirab, N. Hamza, and H. Al-Busaidi, "Design and implementation of smart irrigation system for groundwater use at farm scale," in *Proc. 7th Int. Conf. Modeling, Identificat. Control (ICMIC)*, Sousse, Tunisia, Dec. 2015, pp. 1–6, doi: 10.1109/ICMIC.2015.7409402.

[194] A. Abdullah, S. A. Enazi, and I. Damaj, "AgriSys: A smart and ubiquitous controlled-environment agriculture system," in *Proc. 3rd MEC Int. Conf. Big Data Smart City (ICBDSC)*, Muscat, Oman, Mar. 2016, pp. 1–6, doi: 10.1109/ICBDSC.2016.7460386.

[195] I. Mahmud and N. A. Nafi, "An approach of cost-effective automatic irrigation and soil testing system," in *Proc. Emerg. Technol. Comput., Commun. Electron. (ETCCE)*, Dhaka, Bangladesh, Dec. 2020, pp. 1–5.

[196] D. Singh and A. Thakur, "Designing of smart drip irrigation system for remote hilly areas," in *Proc. 5th Int. Conf. Parallel, Distrib. Grid Comput. (PDGC)*, Dec. 2018, pp. 90–94.

[197] V. V. H. Ram, H. Vishal, S. Dhanalakshmi, and P. M. Vidya, "Regulation of water in agriculture field using Internet of Things," in *Proc. IEEE Technological Innov. ICT Agricult. Rural Develop. (TIAR)*, Jul. 2015, pp. 112–115.

[198] K. M. R. Haque, M. A. Muyeed, S. Sadat, and R. Palit, "Jol-shinchon: Design and development of a sensor based intelligent auto irrigation system," in *Proc. IEEE 7th Annu. Comput. Commun. Workshop Conf. (CCWC)*, Jan. 2017, pp. 1–5.

[199] D. I. Ahmed and X. Fernando, "Solar-powered drip-irrigation for rural Bangladesh," in *Proc. IEEE Canada Int. Hum. Technol. Conf. (IHTC)*, Jul. 2017, pp. 193–196.

[200] R. R. Mudliar, K. A. Mamun, F. R. Islam, and M. Cirrincione, "An approach of reviving papaya production in Fiji using renewable energy powered optimised smart irrigation," in *Proc. 4th Asia–Pacific World Congr. Comput. Sci. Eng. (APWC CSE)*, Dec. 2017, pp. 232–238.

[201] A. Jiang and A. M. Bilton, "Design of a passive irrigation controller for efficient water use in low-income countries," in *Proc. IEEE Global Hum. Technol. Conf. (GHTC)*, Oct. 2017, pp. 1–8.

[202] M. F. M. Azam et al., "Hybrid water pump system for hilly agricultural site," in *Proc. 7th IEEE Control Syst. Graduate Res. Colloq. (ICSGRC)*, Aug. 2016, pp. 109–114.

[203] N. Abdullah et al., "Towards smart agriculture monitoring using fuzzy systems," *IEEE Access*, vol. 9, pp. 4097–4111, 2021.

[204] A. Srivastava, D. K. Das, and R. Kumar, "Monitoring of soil parameters and controlling of soil moisture through IoT based smart agriculture," in *Proc. IEEE Students Conf. Eng. Syst. (SCES)*, Prayagraj, India, Jul. 2020, pp. 1–6.

[205] M. Danita, B. Mathew, N. Shereen, N. Sharon, and J. J. Paul, "IoT based automated greenhouse monitoring system," in *Proc. 2nd Int. Conf. Intell. Comput. Control Syst. (ICICCS)*, Madurai, India, Jun. 2018, pp. 1933–1937.

[206] U. Sakthi and J. D. Rose, "Smart agricultural knowledge discovery system using IoT technology and fog computing," in *Proc. 3rd Int. Conf. Smart Syst. Inventive Technol. (ICSSIT)*, Aug. 2020, pp. 48–53.

[207] M. Sheth and P. Rupani, "Smart gardening automation using IoT with BLYNK app," in *Proc. 3rd Int. Conf. Trends Electron. Informat. (ICOEI)*, Tirunelveli, India, Apr. 2019, pp. 266–270.

[208] S. Pawar, S. Tembe, R. Acharekar, S. Khan, and S. Yadav, "Design of an IoT enabled automated hydroponics system using NodeMCU and blynk," in *Proc. IEEE 5th Int. Conf. for Converg. Technol. (I2CT)*, Mar. 2019, pp. 1–6.

[209] Y. Kuang, Y. Shen, L. Lu, and G. Li, "Farmland monitoring system based on cloud platform," in *Proc. IEEE 8th Joint Int. Inf. Technol. Artif. Intell. Conf. (ITAIC)*, Chongqing, China, May 2019, pp. 335–339.

[210] M. Kalimuthu, P. Vaishnavi, and M. Kishore, "Crop prediction using machine learning," in *Proc. 3rd Int. Conf. Smart Syst. Inventive Technol. (ICSSIT)*, Tirunelveli, India, Aug. 2020, pp. 926–932, doi: 10.1109/ICSSIT48917.2020.9214190.

[211] L. Boukhris, J. B. Abderrazak, and H. Besbes, "Tailored deep learning based architecture for smart agriculture," in *Proc. Int. Wireless Commun. Mobile Comput. (IWCMC)*, Limassol, Cyprus, Jun. 2020, pp. 964–969.

[212] 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 *Proc. Int. Conf. Omni-Layer Intell. Syst. (COINS)*, Aug. 2020, pp. 1–6.

[213] F. M. Ribeiro, R. Prati, R. Bianchi, and C. Kamienski, "A nearest neighbors based data filter for fog computing in IoT smart agriculture," in *Proc. IEEE Int. Workshop Metrol. Agricult. Forestry (MetroAgriFor)*, Nov. 2020, pp. 63–67.

[214] A. Carvalho, N. O'Mahony, L. Krpalkova, S. Campbell, J. Walsh, and P. Doody, "Farming on the edge: Architectural goals," in *Proc. 8th Int. Conf. Agro-Geoinformat. (Agro-Geoinformatics)*, Jul. 2019, pp. 1–6.

[215] A. Brogi, S. Forti, and A. Ibrahim, "How to best deploy your fog applications, probably," in *Proc. IEEE 1st Int. Conf. Fog Edge Comput. (ICFEC)*, May 2017, pp. 105–114.

[216] R. Saha, A. Chakraborty, S. Misra, S. K. Das, and C. Chatterjee, "DLSense: Distributed learning-based smart virtual sensing for precision agriculture," *IEEE Sensors J.*, vol. 21, no. 16, pp. 17556–17563, Aug. 2021.

[217] G. Codeluppi, A. Cilfone, L. Davoli, and G. Ferrari, "AI at the edge: A smart gateway for greenhouse air temperature forecasting," in *Proc. IEEE Int. Workshop Metrol. Agricult. Forestry (MetroAgriFor)*, Nov. 2020, pp. 348–353.

[218] P. Chun-Ting, L. Meng-Ju, H. Nen-Fu, L. Jhong-Ting, and S. Jia-Jung, "Agriculture blockchain service platform for farm-to-fork traceability with IoT sensors," in *Proc. Int. Conf. Inf. Netw. (ICOIN)*, Jan. 2020, pp. 158–163.

[219] D.-H. Nguyen, N. H. Tuong, and H.-A. Pham, "Blockchain-based farming activities tracker for enhancing trust in the community supported agriculture model," in *Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC)*, Oct. 2020, pp. 737–740.

[220] C. Yang and Z. Sun, "Data management system based on blockchain technology for agricultural supply chain," in *Proc. Int. Conf. Data Mining Workshops (ICDMW)*, Nov. 2020, pp. 907–911.

[221] H.-T. Wu and C.-W. Tsai, "An intelligent agriculture network security system based on private blockchains," *J. Commun. Netw.*, vol. 21, no. 5, pp. 503–508, Oct. 2019.

[222] S. S. L. Chukkapalli, A. Piplai, S. Mittal, M. Gupta, and A. Joshi, "A smart-farming ontology for attribute based access control," in *Proc. IEEE IEEE 6th Int. Conf. Big Data Secur. Cloud (BigDataSecurity) Int. Conf. High Perform. Smart Comput., (HPSC) IEEE Int. Conf. Intell. Data Secur. (IDS)*, May 2020, pp. 29–34.

[223] C. Radu, E. Apostol, C. Leordeanu, and M. Mocanu, "Integrated cloud framework for farm management," in *Proc. 10th Int. Conf. Complex, Intell., Softw. Intensive Syst. (CISIS)*, Jul. 2016, pp. 302–307.

[224] G. Manogaran, M. Alazab, K. Muhammad, and V. H. C. de Albuquerque, "Smart sensing based functional control for reducing uncertainties in agricultural farm data analysis," *IEEE Sensors J.*, vol. 21, no. 16, pp. 17469–17478, Aug. 2021.

[225] P. V. Astillo, J. Kim, V. Sharma, and I. You, "SGF-MD: Behavior rule specification-based distributed misbehavior detection of embedded IoT devices in a closed-loop smart greenhouse farming system," *IEEE Access*, vol. 8, pp. 196235–196252, 2020.

[226] R. Khan, M. Zakarya, V. Balasubramanian, M. A. Jan, and V. G. Menon, "Smart sensing-enabled decision support system for water scheduling in orange orchard," *IEEE Sensors J.*, vol. 21, no. 16, pp. 17492–17499, Aug. 2021, doi: 10.1109/JSEN.2020.3012511.

[227] R. Khan, I. Ali, M. Zakarya, M. Ahmad, M. Imran, and M. Shoaib, "Technology-assisted decision support system for efficient water utilization: A real-time testbed for irrigation using wireless sensor networks," *IEEE Access*, vol. 6, pp. 25686–25697, 2018.

[228] N. K. Choudhary, S. S. L. Chukkapalli, S. Mittal, M. Gupta, M. Abdelsalam, and A. Joshi, "YieldPredict: A crop yield prediction framework for smart farms," in *Proc. IEEE Int. Conf. Big Data*, Dec. 2020, pp. 2340–2349.

[229] M. Al-Hasan, H. M. Kafi, M. A. Rizvee, M. Hasan, and M. M. Rashid, "Context-aware computing for balanced agricultural production using machine learning," in *Proc. 11th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, Kharagpur, India, Jul. 2020, pp. 1–6.

[230] P. S. Nishant, P. S. Venkat, B. L. Avinash, and B. Jabber, "Crop yield prediction based on Indian agriculture using machine learning," in *Proc. Int. Conf. Emerg. Technol. (INCET)*, Belgaum, India, Jun. 2020, pp. 1–4.

[231] S. Nguyen-Xuan and N. L. Nhat, "A dynamic model for temperature prediction in glass greenhouse," in *Proc. 6th NAFOSTED Conf. Inf. Comput. Sci. (NICS)*, Dec. 2019, pp. 274–278.

[232] M. T. Shakoor, K. Rahman, S. N. Rayta, and A. Chakrabarty, "Agricultural production output prediction using supervised machine learning techniques," in *Proc. 1st Int. Conf. Next Gener. Comput. Appl. (NextComp)*, Jul. 2017, pp. 182–187.

[233] D. V. Savla, A. N. Parab, K. Y. Kekre, J. P. Gala, S. Ramchandra, and P. A. Sonawane, "Virtual farmer: Real time crop prediction and automatic irrigation system," in *Proc. 11th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, Kharagpur, India, Jul. 2020, pp. 1–5.

[234] R. Nikhil, B. S. Anisha, and R. Kumar P., "Real-time monitoring of agricultural land with crop prediction and animal intrusion prevention using Internet of Things and machine learning at edge," in *Proc. IEEE Int. Conf. Electron., Comput. Commun. Technol. (CONECCT)*, Bengaluru, India, Jul. 2020, pp. 1–6.

[235] R. Reshma, V. Sathiyavathi, T. Sindhu, K. Selvakumar, and L. SaiRamesh, "IoT based classification techniques for soil content analysis and crop yield prediction," in *Proc. 4th Int. Conf. I-SMAC (IoT Social, Mobile, Analytics Cloud) (I-SMAC)*, Palladam, India, Oct. 2020, pp. 156–160.

[236] M. H. Jumat, M. S. Nazmudeen, and A. T. Wan, "Smart farm prototype for plant disease detection, diagnosis & treatment using IoT device in a greenhouse," in *Proc. 7th Brunei Int. Conf. Eng. Technol. (BICET)*, 2018, p. 4, doi: 10.1049/cp.2018.1545.

[237] S. K. Lenka and A. G. Mohapatra, "Gradient descent with momentum based neural network pattern classification for the prediction of soil moisture content in precision agriculture," in *Proc. IEEE Int. Symp. Nanoelectron. Inf. Syst.*, Dec. 2015, pp. 63–66.

[238] S. B. C. S. Putro, I. W. Mustika, and L. E. Nugroho, "Optimized back-propagation artificial neural network algorithm for smart agriculture applications," in *Proc. 4th Int. Conf. Sci. Technol. (ICST)*, Aug. 2018, pp. 1–5.

[239] P. Wickramaarachchi, N. Balasooriya, L. Welipenne, S. Gunasekara, and A. Jayakody, "Real-time greenhouse environmental conditions optimization using neural network and image processing," in *Proc. 20th Int. Conf. Adv. ICT Emerg. Regions (ICTer)*, Colombo, Sri Lanka, Nov. 2020, pp. 232–237.

[240] J. R. D. Cruz, R. G. Baldovino, A. A. Bandala, and E. P. Dadios, "Water usage optimization of smart farm automated irrigation system using artificial neural network," in *Proc. 5th Int. Conf. Inf. Commun. Technol. (ICoIC7)*, Melaka, Malaysia, May 2017, pp. 1–5, doi: 10.1109/ICoICT.2017.8074668.

[241] M. Rebortera and A. Fajardo, "Forecasting banana harvest yields using deep learning," in *Proc. IEEE 9th Int. Conf. Syst. Eng. Technol. (ICSET)*, Shah Alam, Malaysia, Oct. 2019, pp. 380–384, doi: 10.1109/ICSEngT.2019.8906427.

[242] B. Arora, D. S. Chaudhary, M. Satsangi, M. Yadav, L. Singh, and P. S. Sudhish, "Agribot: A natural language generative neural networks engine for agricultural applications," in *Proc. Int. Conf. Contemp. Comput. Appl. (IC3A)*, Lucknow, India, Feb. 2020, pp. 28–33, doi: 10.1109/IC3A48958.2020.233263.

[243] A. Magsi, J. A. Mahar, M. A. Razzaq, and S. H. Gill, "Date palm disease identification using features extraction and deep learning approach," in *Proc. IEEE 23rd Int. Multitopic Conf. (INMIC)*, Nov. 2020, pp. 1–6, doi: 10.1109/INMIC50486.2020.9318158.

[244] L. Ale, A. Sheta, L. Li, Y. Wang, and N. Zhang, "Deep learning based plant disease detection for smart agriculture," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, Waikoloa, HI, USA, Dec. 2019, pp. 1–6, doi: 10.1109/GCWkshps45667.2019.9024439.

[245] S. Shorewala, A. Ashfaque, R. Sidharth, and U. Verma, "Weed density and distribution estimation for precision agriculture using semi-supervised learning," *IEEE Access*, vol. 9, pp. 27971–27986, 2021.

[246] H. Kuzuhara, H. Takimoto, Y. Sato, and A. Kanagawa, "Insect pest detection and identification method based on deep learning for realizing a pest control system," in *Proc. 59th Annu. Conf. Soc. Instrum. Control Eng. Jpn. (SICE)*, Chiang Mai, Thailand, Sep. 2020, pp. 709–714.

[247] R. Tombe, "Computer vision for smart farming and sustainable agriculture," in *Proc. IST-Afr. Conf. (IST-Africa)*, 2020, pp. 1–8.

[248] F. de Vita, G. Nocera, D. Bruneo, V. Tomaselli, D. Giacalone, and S. K. Das, "Quantitative analysis of deep leaf: A plant disease detector on the smart edge," in *Proc. IEEE Int. Conf. Smart Comput. (SMART-COMP)*, Bologna, Italy, Sep. 2020, pp. 49–56.

[249] C.-J. Chen, Y.-Y. Huang, Y.-S. Li, C.-Y. Chang, and Y.-M. Huang, "An AIoT based smart agricultural system for pests detection," *IEEE Access*, vol. 8, pp. 180750–180761, 2020.

[250] Y. Beeharry and V. Bassoo, "Performance of ANN and AlexNet for weed detection using UAV-based images," in *Proc. 3rd Int. Conf. Emerg. Trends Electr., Electron. Commun. Eng. (ELECOM)*, Balaclava, Mauritius, Nov. 2020, pp. 163–167, doi: 10.1109/ELECOM49001.2020.9296994.

[251] M. N. Gunathilaka, S. Lokuliyana, A. C. Udurawana, D. Dissanayaka, and J. A. Jayakody, "Efficient agricultural sensor network with disease detection," in *Proc. Int. Conf. Adv. Comput. (ICAC)*, Malabe, Sri Lanka, 2019, pp. 446–451, doi: 10.1109/ICAC49085.2019. 9103345.

[252] W. Fan, C. Chong, G. Xiaoling, Y. Hua, and W. Juyun, "Prediction of crop yield using big data," in *Proc. 8th Int. Symp. Comput. Intell. Design (ISCID)*, vol. 1, Dec. 2015, pp. 255–260.

[253] M. Yang, D. Li, M. Chen, A. Bouras, Y. Tang, and X. Yu, "The implementation of a crop diseases APP based on deep transfer learning," in *Proc. 3rd Int. Conf. Artif. Intell. Big Data (ICAIBD)*, Chengdu, China, May 2020, pp. 22–28.

[254] X. Liu, W. Min, S. Mei, L. Wang, and S. Jiang, "Plant disease recognition: A large-scale benchmark dataset and a visual region and loss reweighting approach," *IEEE Trans. Image Process.*, vol. 30, pp. 2003–2015, 2021, doi: 10.1109/TIP.2021.3049334.

[255] N. Putjaika, S. Phusae, A. Chen-Im, P. Phunchongharn, and K. Akkarajitsakul, "A control system in an intelligent farming by using Arduino technology," in *Proc. 5th ICT Int. Student Project Conf. (ICT-ISPC)*, Nakhon Pathom, Thailand, May 2016, pp. 53–56, doi: 10.1109/ICT-ISPC.2016.7519234.

[256] P. Bir, R. Kumar, and G. Singh, "Transfer learning based tomato leaf disease detection for mobile applications," in *Proc. IEEE Int. Conf. Comput., Power Commun. Technol. (GUCON)*, Greater Noida, India, Oct. 2020, pp. 34–39.

[257] Y. He, F. Pan, B. Wang, Z. Teng, and J. Wu, "Transfer learning based fruits image segmentation for fruit-picking robots," in *Proc. IEEE 3rd Int. Conf. Comput. Commun. Eng. Technol. (CCET)*, Beijing, China, Aug. 2020, pp. 71–75.

[258] K. Guravaiah and S. S. Raju, "e-Agriculture: Irrigation system based on weather forecasting," in *Proc. IEEE 15th Int. Conf. Ind. Inf. Syst. (ICIIS)*, Rupnagar, India, Nov. 2020, pp. 617–622, doi: 10.1109/ICIIS51140.2020.9342739.

[259] B. R. Prakash and S. S. Kulkarni, "Super smart irrigation system using Internet of Things," in *Proc. 7th Int. Conf. Smart Struct. Syst. (ICSSS)*, Jul. 2020, pp. 1–5.

[260] A. Anitha, N. Sampath, and M. A. Jerlin, "Smart irrigation system using Internet of Things," in *Proc. Int. Conf. Emerg. Trends Inf. Technol. Eng. (ic-ETITE)*, Feb. 2020, pp. 1–7.

[261] S. Peraka, R. Sudheer, B. N. Rao, A. R. Teja, and E. N. Kumar, "Smart irrigation based on crops using IoT," in *Proc. IEEE 15th Int. Conf. Ind. Inf. Syst. (ICIIS)*, Rupnagar, India, Nov. 2020, pp. 611–616, doi: 10.1109/ICIIS51140.2020.9342736.

[262] J. S. Sujin, R. Murugan, M. Nagarjun, and A. K. Praveen, "IoT based greenhouse monitoring and controlling system," *J. Phys., Conf. Ser.*, vol. 1916, no. 1, May 2021, Art. no. 012062, doi: 10.1088/1742-6596/1916/1/012062.

[263] X. Fei, W. Xiao-Long, and X. Yong, "Development of energy saving and rapid temperature control technology for intelligent greenhouses," *IEEE Access*, vol. 9, pp. 29677–29685, 2021.

[264] S. Yan-Fang, S. Jian-Guo, and X. Yu-Qian, "Design and application of distributed intelligent greenhouse computerized system," in *Proc. 7th Int. Conf. Measuring Technol. Mechatronics Autom.*, Nanchang, China, 2015, pp. 331–334.

[265] T. Nazir, M. Arslan, and U. S. Khan, "Design of an automated greenhouse temperature controller; a renewable, robust and cost effective scheme," in *Proc. 5th Int. Conf. Control, Autom. Robot. (ICCAR)*, Beijing, China, Apr. 2019, pp. 342–346, doi: 10.1109/ICCAR.2019.8813324.

[266] S. Khummanee, S. Wiangsamut, P. Sorntepa, and C. Jaiboon, "Automated smart farming for orchids with the Internet of Things and fuzzy logic," in *Proc. Int. Conf. Inf. Technol. (InCIT)*, Oct. 2018, pp. 1–6.

[267] F. Rahman, I. J. Ritun, M. R. A. Biplob, N. Farhin, and J. Uddin, "Automated aeroponics system for indoor farming using Arduino," in *Proc. Joint 7th Int. Conf. Informat., Electron. Vis. (ICIEV) 2nd Int. Conf. Imag., Vis. Pattern Recognit. (icIVPR)*, Kitakyushu, Japan, Jun. 2018, pp. 137–141, doi: 10.1109/ICIEV.2018. 8641026.

[268] N. Lekbangpong, J. Muangprathub, T. Srisawat, and A. Wanichsombat, "Precise automation and analysis of environmental factor effecting on growth of St. John's wort," *IEEE Access*, vol. 7, pp. 112848–112858, 2019, doi: 10.1109/ACCESS.2019.2934743.

[269] B. Al-Beeshi, B. Al-Mesbah, S. Al-Dosari, and M. El-Abd, "iPlant: The greenhouse robot," in *Proc. IEEE 28th Can. Conf. Electr. Comput. Eng. (CCECE)*, Halifax, NS, Canada, May 2015, pp. 1489–1494, doi: 10.1109/CCECE.2015.7129501.

[270] I. Mat, M. R. M. Kassim, A. N. Harun, and I. M. Yusoff, "Smart agriculture using Internet of Things," in *Proc. IEEE Conf. Open Syst. (ICOS)*, Langkawi, Malaysia, Nov. 2018, pp. 54–59.

[271] T. Changmai, S. Gertphol, and P. Chulak, "Smart hydroponic lettuce farm using Internet of Things," in *Proc. 10th Int. Conf. Knowl. Smart Technol. (KST)*, Chiang Mai, Thailand, Jan. 2018, pp. 231–236, doi: 10.1109/KST.2018.8426141.

[272] M. Ajay, M. Rakesh, M. H. Roshan, and G. Revathy, "PLC based smart farming system with scada," in *Proc. IEEE Int. Conf. Adv. Develop. Electr. Electron. Eng. (ICADEE)*, Coimbatore, India, Dec. 2020, pp. 1–2.

[273] H. Wang, J. Zhao, J. Duan, M. Wang, and Z. Dong, "Greenhouse CO_2 control based on improved genetic algorithm and fuzzy neural network," in *Proc. 2nd IEEE Adv. Inf. Manag., Commun., Electron. Autom. Control Conf. (IMCEC)*, Xi'an, China, May 2018, pp. 1537–1540.

[274] O. Chieochan, A. Saokaew, and E. Boonchieng, "IoT for smart farm: A case study of the Lingzhi mushroom farm at Maejo University," in *Proc. 14th Int. Joint Conf. Comput. Sci. Softw. Eng. (JCSSE)*, Nakhon Si Thammarat, Thailand, Jul. 2017, pp. 1–6, doi: 10.1109/JCSSE.2017.8025904.

[275] A. Math, L. Ali, and U. Pruthviraj, "Development of smart drip irrigation system using IoT," in *Proc. IEEE Distrib. Comput., VLSI, Electr. Circuits Robot. (DISCOVER)*, Mangalore, India, Aug. 2018, pp. 126–130, doi: 10.1109/DISCOVER.2018. 8674080.

[276] A. Islam, K. Akter, N. J. Nipu, A. Das, M. M. Rahman, and M. Rahman, "IoT based power efficient agro field monitoring and irrigation control system: An empirical implementation in precision agriculture," in *Proc. Int. Conf. Innov. Sci., Eng. Technol. (ICISET)*, Chittagong, Bangladesh, Oct. 2018, pp. 372–377.

[277] M. R. H. Naeem, S. Gawhar, M. B. H. Adib, S. A. Sakib, A. Ahmed, and N. A. Chisty, "An IoT based smart irrigation system," in *Proc. 2nd Int. Conf. Robot., Electr. Signal Process. Techn. (ICREST)*, Dhaka, Bangladesh, Jan. 2021, pp. 243–247, doi: 10.1109/ICREST51555.2021.9331092.

[278] S. Pallavi, J. D. Mallapur, and K. Y. Bendigeri, "Remote sensing and controlling of greenhouse agriculture parameters based on IoT," in *Proc. Int. Conf. Big Data, IoT Data Sci. (BID)*, Pune, India, Dec. 2017, pp. 44–48, doi: 10.1109/BID.2017.8336571.

[279] X. Cui et al., "Design and experiment of control system for intelligent agriculture based on Arduino," in *Proc. IEEE 9th Joint Int. Inf. Technol. Artif. Intell. Conf. (ITAIC)*, Chongqing, China, Dec. 2020, pp. 2297–2300, doi: 10.1109/ITAIC49862.2020.9338949.

[280] U. Shandilya and V. Khanduja, "Intelligent farming system with weather forecast support and crop prediction," in *Proc. 5th Int. Conf. Comput., Commun. Secur. (ICCCS)*, Patna, India, Oct. 2020, pp. 1–6, doi: 10.1109/ICCCS49678.2020.9277437.

[281] P. B. Wakhare, S. Neduncheliyan, and G. S. Sonawane, "Automatic irrigation system based on Internet of Things for crop yield prediction," in *Proc. Int. Conf. Emerg. Smart Comput. Informat. (ESCI)*, Pune, India, Mar. 2020, pp. 129–132.

[282] M. Farooq, A. Hussain, S. Hashim, L. Yang, and M. Ali, "Automated irrigation system based on irrigation gates using fuzzy logic," in *Proc. Int. Conf. Internet Things Intell. Appl. (ITIA)*, Zhenjiang, China, Nov. 2020, pp. 1–5.

[283] B. Et-taibi, M. R. Abid, I. Boumhidi, and D. Benhaddou, "Smart agriculture as a cyber physical system: A real-world deployment," in *Proc. 4th Int. Conf. Intell. Comput. Data Sci. (ICDS)*, Fes, Morocco, Oct. 2020, pp. 1–7.

[284] R. Zhao, Y. Ding, S. Ma, and M. Wang, "Design of intelligent greenhouse control system based on Internet of Things," in *Proc. 2nd Int. Conf. Inf. Syst. Comput. Aided Educ. (ICISCAE)*, Sep. 2019, pp. 117–121.

[285] H. Benyezza, M. Bouhedda, M. C. Zerhouni, M. Boudjemaa, and S. A. Dura, "Fuzzy greenhouse temperature and humidity control based on Arduino," in *Proc. Int. Conf. Appl. Smart Syst. (ICASS)*, Médéa, Algeria, Nov. 2018, pp. 1–6.

[286] X. Xing, J. Song, L. Lin, M. Tian, and Z. Lei, "Development of intelligent information monitoring system in greenhouse based on wireless sensor network," in *Proc. 4th Int. Conf. Inf. Sci. Control Eng. (ICISCE)*, Changsha, China, Jul. 2017, pp. 970–974.

[287] Y. Alaviyan, M. Aghaseyedabdollah, M. Sadafi, and A. Yazdizade, "Design and manufacture of a smart greenhouse with supervisory control of environmental parameters using fuzzy inference controller," in *Proc. 6th Iranian Conf. Signal Process. Intell. Syst. (ICSPIS)*, Mashhad, Iran, Dec. 2020, pp. 1–6.

[288] Ö. Alpay and E. Erdem, "Climate control of an smart greenhouse based on android," in *Proc. Int. Conf. Artif. Intell. Data Process. (IDAP)*, Malatya, Turkey, Sep. 2018, pp. 1–5.

[289] H. Benyezza, M. Bouhedda, N. Faci, M. Aissani, and S. Rebouh, "Greenhouse monitoring and fuzzy control system based on WSAN and IoT," in *Proc. Int. Conf. Appl. Autom. Ind. Diag. (ICAAID)*, vol. 1, Elâziğ, Turkey, Sep. 2019, pp. 1–5.

[290] R. Yadav and A. K. Daniel, "Fuzzy based smart farming using wireless sensor network," in *Proc. 5th IEEE Uttar Pradesh Sect. Int. Conf. Electr., Electron. Comput. Eng. (UPCON)*, Gorakhpur, India, Nov. 2018, pp. 1–6.

[291] M. A. Elashiri and A. T. Shawky, "Fuzzy smart greenhouses using IoT," in *Proc. IEEE Int. Conf. Comput. Intell. Comput. Res. (ICCIC)*, Madurai, India, Dec. 2018, pp. 1–4.

[292] V. Ramachandran, R. Ramalakshmi, and S. Srinivasan, "An automated irrigation system for smart agriculture using the Internet of Things," in *Proc. 15th Int. Conf. Control, Autom., Robot. Vis. (ICARCV)*, Singapore, Nov. 2018, pp. 210–215.

[293] D. Guidotti, S. Marchi, S. Antognelli, and A. Cruciani, "Water management: Agricolus tools integration," in *Proc. Global IoT Summit (GIoTS)*, Aarhus, Denmark, Jun. 2019, pp. 1–5.

[294] R. N. Kirtana, B. Bharathi, S. K. Priya, S. Kavitha, B. Keerthana, and K. Kripa, "Smart irrigation system using zigbee technology and machine learning techniques," in *Proc. Int. Conf. Intell. Comput. Commun. Smart World (I2C2SW)*, Erode, India, Dec. 2018, pp. 78–82.

[295] M. I. Alipio, A. E. M. D. Cruz, J. D. A. Doria, and R. M. S. Fruto, "A smart hydroponics farming system using exact inference in Bayesian network," in *Proc. IEEE 6th Global Conf. Consum. Electron. (GCCE)*, Nagoya, Japan, Oct. 2017, pp. 1–5.

[296] G. Nakanishi and H. Mineno, "Examination of image features considering short-term changes in plant water stress," in *Proc. IEEE 9th Global Conf. Consum. Electron. (GCCE)*, Kobe, Japan, Oct. 2020, pp. 743–744.

[297] R. K. Jain, B. Gupta, M. Ansari, and P. P. Ray, "IoT enabled smart drip irrigation system using web/Android applications," in *Proc. 11th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, Kharagpur, India, Jul. 2020, pp. 1–6.

[298] H. Meena, H. Nandanwar, D. Pahl, and A. Chauhan, "IoT based perceptive monitoring and controlling an automated irrigation system," in *Proc. 11th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, Kharagpur, India, Jul. 2020, pp. 1–6.

[299] T. Xiong and S. Wang, "Intelligent farm management and control system based on Raspberry Pi," in *Proc. IEEE 3rd Adv. Inf. Manag., Commun., Electron. Autom. Control Conf. (IMCEC)*, Chongqing, China, Oct. 2019, pp. 1286–1290.

[300] B. Ramesh, M. Divya, and G. P. Revathi, "Farm Easy- IoT based automated irrigation, monitoring and pest detection using ThingSpeak for analysis of ladies finger plant," in *Proc. Int. Conf. Recent Trends Electron., Inf., Commun. Technol. (RTEICT)*, Bengaluru, India, Nov. 2020, pp. 237–241.

[301] T. Namgyel et al., "IoT based hydroponic system with supplementary LED light for smart home farming of lettuce," in *Proc. 15th Int. Conf. Electr. Eng./Electron., Comput., Telecommun. Inf. Technol. (ECTI-CON)*, Jul. 2018, pp. 221–224.

[302] R. K. Kodali, S. Soratkal, and L. Boppana, "IoT based control of appliances," in *Proc. Int. Conf. Comput., Commun. Autom. (ICCCA)*, Greater Noida, India, Apr. 2016, pp. 1293–1297.

[303] J. C. D. Lara, S. Gutierrez, and F. Rodríguez, "Low cost greenhouse monitoring system based on Internet of Things," in *Proc. IEEE Int. Conf. Eng. Veracruz (ICEV)*, Boca del Río, Mexico, Oct. 2019, pp. 1–6.

[304] L. Li, K. W. E. Cheng, and J. F. Pan, "Design and application of intelligent control system for greenhouse environment," in *Proc. 7th Int. Conf. Power Electron. Syst. Appl. Smart Mobility, Power Transf. Secur. (PESA)*, Hong Kong, Dec. 2017, pp. 1–5.

[305] V. Kumar, H. Arora, Harsh, and J. Sisodia, "ResNet-based approach for detection and classification of plant leaf diseases," in *Proc. Int. Conf. Electron. Sustain. Commun. Syst. (ICESC)*, Coimbatore, India, Jul. 2020, pp. 495–502.

[306] A. Tendolkar and S. Ramya, "CareBro (personal farm assistant): An IoT based smart agriculture with edge computing," in *Proc. 3rd Int. Conf. Multimedia Process., Commun. Inf. Technol. (MPCIT)*, Shivamogga, India, Dec. 2020, pp. 97–102.

[307] F.-H. Tseng, H.-H. Cho, and H.-T. Wu, "Applying big data for intelligent agriculture-based crop selection analysis," *IEEE Access*, vol. 7, pp. 116965–116974, 2019, doi: 10.1109/ACCESS.2019. 2935564.

[308] Y.-P. Huang, T.-H. Wang, and H. Basanta, "Using fuzzy mask R-CNN model to automatically identify tomato ripeness," *IEEE Access*, vol. 8, pp. 207672–207682, 2020, doi: 10.1109/ACCESS.2020.3038184.

[309] P. S. B. C. Suryo, I. W. Mustika, O. Wahyunggoro, and H. S. Wasisto, "Improved time series prediction using LSTM neural network for smart agriculture application," in *Proc. 5th Int. Conf. Sci. Technol. (ICST)*, Yogyakarta, Indonesia, Jul. 2019, pp. 1–4.

[310] M. R. Bendre, R. C. Thool, and V. R. Thool, "Big data in precision agriculture: Weather forecasting for future farming," in *Proc. 1st Int. Conf. Next Gener. Comput. Technol. (NGCT)*, Dehradun, India, Sep. 2015, pp. 744–750.

[311] D. Shadrin, A. Menshchikov, D. Ermilov, and A. Somov, "Designing future precision agriculture: Detection of seeds germination using artificial intelligence on a low-power embedded system," *IEEE Sensors J.*, vol. 19, no. 23, pp. 11573–11582, Dec. 2019.

[312] J. Alejandrino et al., "Visual classification of lettuce growth stage based on morphological attributes using unsupervised machine learning models," in *Proc. IEEE REGION 10 Conf. (TENCON)*, Osaka, Japan, Nov. 2020, pp. 438–443.

[313] P. J. Loresco, I. Valenzuela, A. Culaba, and E. Dadios, "Viola–Jones method of marker detection for scale-invariant calculation of lettuce leaf area," in *Proc. IEEE 10th Int. Conf. Hum., Nanotechnol., Inf. Technol., Commun. Control, Environ. Manag. (HNICEM)*, Baguio, Philippines, Nov. 2018, pp. 1–5.

[314] C. K. G. Albuquerque, S. Polimante, A. Torre-Neto, and R. C. Prati, "Water spray detection for smart irrigation systems with mask R-CNN and UAV footage," in *Proc. IEEE Int. Workshop Metrol. Agricult. Forestry (MetroAgriFor)*, Nov. 2020, pp. 236–240.

[315] Y. Huang, L. Qin, G. Wu, and C. Shi, "Research on Android-based video monitoring for greenhouse devices status," in *Proc. Chin. Control Conf. (CCC)*, Guangzhou, China, Jul. 2019, pp. 6404–6409.

[316] M. D. Bah, A. Hafiane, and R. Canals, "CRowNet: Deep network for crop row detection in UAV images," *IEEE Access*, vol. 8, pp. 5189–5200, 2020, doi: 10.1109/ACCESS.2019.2960873.

Nabila Elbeheiry (Member, IEEE) received the B.S. degree in electrical and computer engineering from the Texas A&M University at Qatar, Doha, Qatar. She is currently pursuing the M.S. degree from the Texas A&M University, College Station, TX, USA.

Her current research areas include photovoltaic integration with the power grid, power electronic converters and controllers, and machine learning techniques for power and energy systems.

Ms. Elbeheiry has served as the Corresponding Secretary of the Eta-Kappa-Nu Honor Society, the Lambda Mu Student Chapter, and the Program Chair of the IEEE Student Organization in 2019 and 2020.

Robert S. Balog (Senior Member, IEEE) received the B.S. degree in electrical engineering from the Rutgers—The State University of New Jersey, New Brunswick, NJ, USA, in 1996, and the M.S. and Ph.D. degrees in electrical engineering from the University of Illinois at Urbana–Champaign, Urbana, IL, USA, in 2003 and 2006, respectively.

From 1996 to 1999, he was an Engineer with Lutron Electronics, Coopersburg, PA, USA. From 2005 to 2006, he was a Researcher with the Construction Engineering Research Laboratory, Engineering Research and Development Center, U.S. Army Corps of Engineers, Champaign, IL, USA. From 2006 to 2009, he was a Senior Engineer with SunPower Inc., Champaign. Then, he joined Texas A&M University, College Station, TX, USA, where he is currently a Professor with the Department of Electrical and Computer Engineering and the Director of the Renewable Energy and Advanced Power Electronics Research Laboratory. He is a Registered Professional Engineer in Illinois. He holds a joint faculty appointment with the Department of Electrical Engineering, Texas A&M University at Qatar, Doha, Qatar. He holds 20 issued U.S. patents with additional patents pending. His current research interests include power converters for solar energy, particularly microinverters for ac photovoltaic modules and highly reliable electrical power, and energy systems, including dc microgrids.

Dr. Balog is a member of Eta Kappa Nu, Sigma Xi, the National Society of Professional Engineers, the American Solar Energy Society, and the Solar Electric Power Association. He was a recipient of the Rutgers School of Engineering Distinguished Engineer Award in 2011.