Big Data Analytics, Data Science, ML&AI for Connected, Data-driven Precision Agriculture and Smart Farming Systems: Challenges and Future Directions

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ABSTRACT

Big data and data scientific applications in the modern agriculture are rapidly evolving as the data technology advances and more computational power becomes available. The adoption of big data has enabled farmers and producers to optimize their agricultural activities sustainably with cutting-edge technologies, resulting in eco-friendly and efficient farming. Wireless sensor networks and machine learning have had a direct impact on smart and precision agriculture, with deep learning techniques applied to data collected via sensor nodes. Additionally, internet of things, drones, and robotics are being incorporated into farming techniques. Digital data handling has amplified the information wave, and information and communication technology have been used to deliver benefits to both farmers and consumers. This work highlights the technological implications and challenges that arise in data-driven agricultural practices as well as the research problems that need to be solved.

CCS CONCEPTS

• **Applied computing**; • **Computers in other domains**; • **Agriculture**;

KEYWORDS

Big data, Data analytics, Data science, Precision agriculture, Smart farming systems

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1 INTRODUCTION

The agricultural industry has experienced tremendous changes over the years. Traditional farming practices have been replaced by *smart farming*, which uses technology to increase food production more effectively and efficiently. Along with advanced transportation technology, innovations in communication tools and software engineering started to be incorporated into food and agricultural industries. This new kind of farming, known as agriculture 4.0, has been revolutionizing the food and agricultural sectors, addressing some of the problems from the earlier generations. Historically, agriculture 1.0 and 2.0 required traditional and manual labors of human and domesticated animals. Since agriculture 3.0, farming practices and its capacity started to improve by utilizing technology. In agriculture 4.0, technology is completely changing how we do agriculture. For instance, researchers are working on automatic disease diagnosis using computer vision although it is still challenging and error-prone due to various non-infectious and infectious pathogenic agents that can cause similar symptoms in crops. Researchers showed how swarm intelligence can be used to deal with some of the challenges involved in smart farming. Others also looked at how blockchain technology can be used to create transparent smart contracts and to improve the food supply chain. Big data analytics, data science, machine learning (ML) and artificial intelligence (AI) are also being used to develop *precision agriculture* and other agricultural applications [25]. This work reviews and investigates the latest developments and future directions of smart farming and agrotech. These include big data analytics, data science, ML and AI, deep learning (based on neural networks), internet-of-things (IoT), block chain technology, robotics, autonomous systems, and swarm intelligence; see Figure 1 for an illustrative summary.

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2 PRECISION AGRICULTURE & SMART FARMING SYSTEMS

The modern agriculture is undergoing a transformation by collecting and analyzing data to inform smarter farming decisions. Combination of different computational techniques, such as ML and deep learning (DL) in conjunction with sensor networks, are making the agricultural system smarter and more efficient [19, 32, 34]. Precision agriculture has also brought a heightened degree of competition for input supply firms. In this section, we highlight many of the technological and data scientific advancements that made precision agriculture and smart farming systems a reality.

2.1 Big Data

Big data is a research field of analyzing large amounts of data, characterized by volume, velocity, variety, veracity, etc. Precision agriculture emphasizes the collection and utilization of data to make decisions for agricultural value creations. There are many different sources of big data, including ground sensors, historical data collected by governmental and non-governmental agencies, web services, and online repositories. Over the past decade, agricultural

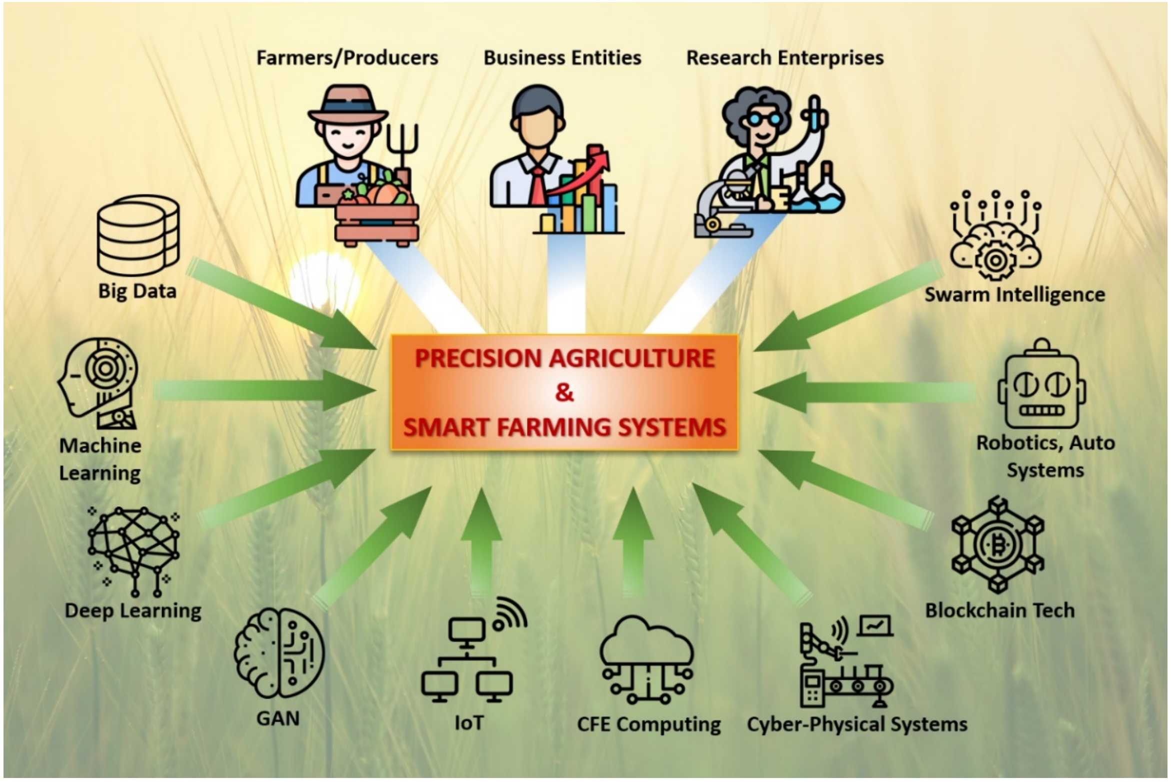

Figure 1: The current state of the art for connected, data-driven precision agriculture and smart farming systems

production has seen a lot of growth due to the increasing use of data from sensors and IoT devices [14, 24]. This data is used to analyze food production patterns, processing, and supply chains. Big data helps producers know what crops to plant and how to produce the most food possible. Sawant et al. [30] designed platforms that connect supply chain actors with quality products and processes. Karmas et al. [17] studied different methods of high-throughput to provide detailed information about interactions between plants and the environment. The study by Gutiérrez et al. [13] looked at self-operating and data-intensive production systems such as indoor LED-illuminated aeroponics and greenhouses. Love et al. [21] demonstrated how these systems can be used to control pests.

2.2 Machine Learning

ML is a technique to help understand the patterns in data. Whether descriptive, predictive or even prescriptive, it is important to choose the right data when constructing ML models, and doing so requires a lot of thought. In supervised learning, labeled data is used to train a model. There are numerous algorithms that can be used for classification such as multiple logistic regression, support vector machines (SVM), decision trees, random forests, naive Bayes, and artificial neural networks (ANN). On the other hand, unsupervised learning algorithms are used to identify patterns in data without being given any labels for classifications. These algorithms can be used to identify trends or relationships in data sets through grouping and clustering. Semi-supervised ML models are trained using both labeled and unlabeled data. In order to handle the unlabeled data, some relationships need to be established between the data distributions. Reinforcement learning (RL) is a type of ML used to decide the best course of action given a situation or environment by rewarding desired behaviors and/or punishing undesired ones. It deals with the sequential decision-making problem in uncertain and unknown environments through learning by practice. There are two different models used for this purpose: Markov decision process (MDP) and Q-learning. The RL approach uses hit and trial methods to help the agents learn within the environment.

As agricultural practices have become more complex, smart farming is the cutting-edge technology that can help farmers deal with the challenges of today. However, fast and optimal decision-making process is still a challenge at the regional and national levels [7]. Additionally, an accurate prediction model is required to decide the type and timing of crops. Elavarasan et al. [2] studied how atmospheric conditions affect crop production using ML models, and how ML can be used to manage soil, livestock, and predict when crops are ready to be harvested. Li et al. [2] performed a systematic review of different methods for determining when fruit is ripe and how best to harvest it. Tewari et al. [37] used computer vision to figure out how to spray pesticides at different rates, and Gao [10] developed a ML-based recognition system for spraying areas from unmanned aerial vehicles (UAV).

2.3 Deep Learning

Currently, there is a lot of excitement in the field of DL as the techniques are capable of dealing with complicated problems, helping to improve modern farming practices. Based on ANN, there are various architectures of DL. The convolutional neural network (CNN) is a type of deep feed-forward ANN that helps to simplify a network by reducing its dimensions. Its success has been widely known in computer vision. The recurrent neural network (RNN) is a type of ANN that can remember previous information. It is used to analyze time-series data or longitudinally collected data such as plant phenotyping, leaf area index estimation, soil moisture content prediction, and event date estimation. A deep belief network (DBN) is a model that mixes direct and indirect connections between the layers, meaning that the relationships between different layers are not always clear. It was recently applied to smart farming applications such as forecasting of crop prices, product characteristics, and facial feature extraction [22]. The deep reinforcement learning (DRN) is an evolutionary model that can make systems more self-reliant and intelligent in agricultural fields. Just like RL, the agents are rewarded based on their performance, and the model continues to attempt to improve by making changes to the course of iterations. The deep recurrent Q network uses a linear and non-linear mapping among crop yield, raw data of soil, and groundwater parameters. It differs from other supervised learning algorithms used in yield prediction [11]. In recent years, DL has been used to process images and data in diverse ways. Yang and Xu [42] surveyed DL technologies in the horticultural field and witnessed their increased applications. DL has been especially helpful in smart farming areas such as quality assessments, stress phenotyping, growth monitoring, yield estimation, variety recognition, plant disease prediction, and crop yield prediction [9, 16]. For example, Trong et al. [38] introduced a new way to classify different types of weeds by using various DL models.

2.4 GAN

Generative adversarial network (GAN) is a type of DL technology that works by training two different networks to compete against each other: generator and discriminator. The generator is taught to do things like recognize patterns and create new ones like images while the discriminator tells the generator whether the created image is real or fake. In this way, they can learn to make better decisions even when they do not have a lot of training data. There are different GAN models applied in the agricultural field. For tomato disease identification, Abbas et al. [1] used the conditional GAN to generate a number of synthetic disease images, and then, DenseNet 121 classifier was trained to classify images. Zhao et al. [44] developed a two-stage (double) GAN to classify tomato crop leaf diseases. Zhang et al. [43] developed a method to identify diseases in cucumber leaves in real time by using the activation reconstruction GAN (ARGAN) and the dilated inception CNN (DICNN). Liu et al. [20] proposed a method of identifying grape crops, using a leafGAN model. Arsenovic et al. [3] developed a method for detecting plant diseases in the field, using a style GAN. Förster et al. [8] presented a cycle consistent GAN to track the dynamic behavior of leaf and disease on a daily basis. Wang et al. [39] developed an auxiliary classifier GAN (AC-GAN) for early detection of viruses in crop disease. Wen et al. [40] introduced the enhanced super resolution GAN (ESRGAN) with a transfer learning approach to improve the accuracy of smart farming applications. Bi and Hu [4] introduced Wasserstein GAN with gradient penalty and label smoothing regularization to overcome overfitting problem with limited training datasets.

2.5 Internet-of-Things

The internet-of-things (IoT) technology connects different things together so that information about them can be shared from all over the world via the internet. The use of IoT and DL in wireless sensor networks (WSN) is bringing the next level of agriculture. Whitmore et al. [41] studied the identification techniques, processing and networking capabilities of IoT devices. Research in this area has continued to grow, and IoT has been helping agricultural development more responsive to changing weather patterns. It has used information and communication technology (ICT) to help farmers get the most out of their land and crops, ensuring they are as productive and healthy as possible. The IoT ensures sustainability, profitability, and safeguards for the environment by enabling site-specific agricultural practices. For instance, the smart irrigation system uses IoT to calculate the water needs of urban areas. It notifies when to irrigate crops based on the moisture levels in soil and temperature. This system collects data about humidity, wind direction and temperature within the test bed. Bo and Wang [5] also discussed the feasibility and potential of combining cloud computing and IoT for applications in agriculture and forestry.

2.6 Cloud-Fog-Edge Computing

Cloud computing virtually pulls many similar and/or different computer resources that may be closely or distantly located from each other, in order to provide on-demand computing services over the internet. Three different service models of cloud computing are software as a service (SaaS), infrastructure as a service (IaaS), and platform as service (PaaS). Fog nodes have the ability to communicate with other fog nodes and clouds as well as the computing power and storage to process data efficiently. Edge computing is a growing area of technology that enables efficient data processing without a need to upload data to the central node. During the past decades, cloud-fog-edge (CFE) computing have played an important role in transforming the agricultural sector. This allowed to store data remotely, capture data from different sources, automate land records, and make predictions about the weather to support more effective agricultural management and improve the crop production. Alonso et al. [2] developed a new edge computing architecture for monitoring the activities of livestock on dairy farms. This system can improve the dairy industry by making the activities of the livestock more transparent, efficient, and environmentally friendly.

2.7 Cyber-Physical Systems

During the past decades, cyber-physical systems (CPS) have become very good at interacting with the physical world by extending the capabilities of physical objects. This is a major step forward as computer and physical elements are becoming more connected to work together more easily and be more useful. This makes computers more adaptable and efficient, and makes physical objects more reliable and safer. CPS provides a way to gather information about the environment, like soil, humidity, and temperature, in order to help decision-making about what crops to plant on which land. AI on CPS can help predict the market demand on different types of pest control solutions. Right now, we use different methods to control pests (*e.g.*, fences, traps, and rodenticides) but a smart pest control solution was also devised by recognizing the rats' behaviors and activities. CPS helps us understand how crops are growing, what decisions need to be made about the fertilizer use, and how to best use water to accelerate the plant growth. CPS can keep track of the soil moisture levels in the field as well as the information about the trees' water requirements. Song et al. [36] conducted a systematic review of several agriculture CPS such as weather monitoring for frost prevention, soil moisture monitoring for scheduling irrigation, and monitoring the soil contents for effective use of fertilizers. Skobelev et al. [35] applied the revolutionary concept of digital twins for plant growth analysis and effective scheduling of resources.

2.8 Blockchain Technology

The blockchain technology is a distributed ledger system that helps keep track of transactions in a secure, transparent, and immutable manner without a middleman like a bank. It can be used to create a decentralized database that is tamper-proof. Every computer node on the blockchain network must verify every transaction, which ensures that everyone involved in a transaction is accountable. There are many different types of consensus algorithms to check the accuracy of information that goes in and out, and the cryptocurrencies like Bitcoin and Ethereum are used to reward these validators. The technology is already being used in different areas like healthcare facilities, financial services, supply chain management, and digital media transfer. The technology can be also useful for small and medium-sized farms because it supports a secure and trackable food supply chain. Smart contracts are essential for keeping track of the transactions in this system. The digital transformation is made possible with the use of blockchain-based smart contract technologies. In addition, cooperatives can be formed to improve competitiveness in developing countries, allowing farmers to produce crops with a larger value compared to their original crops. This will prevent disputes and conflicts among farmers, allowing cooperatives to work smoothly. This technology can also help to insure crops against unpredictable weather and natural disasters. Caro et al. [6] proposed an AgriBlockIoT traceability system for decentralized smart farming. A generic framework leveraging the small contracts for soybean traceability was constructed by Salah et al. [29]. Utilizing blockchain technologies, Jamil et al. [15] developed and optimized a smart livestock farming system.

2.9 Robotics & Autonomous Systems

Over the last decade, there has been a significant progress in improving agricultural productivity by using UAV, unmanned aircraft system (UAS) or drones, robotics and autonomous systems [28]. Different technologies have been developed to increase the effectiveness and reliability of machines, which has replaced certain human labors. These technologies are being used in different production patterns of smart farming such as plant factories, 3D food printing, aerial spraying, biodiverse farming, and autonomous farming. UAV/UAS in particular has been used for plant counts, plant height, field uniformity, soil water levels, soil temperature and topography/3D mapping. Sharma [33] designed a framework to help reduce the waste in the food supply chain while Ghafar et al. [12] designed a robot that can spray fertilizers and insecticides more efficiently, saving costs and eliminating safety risks. Polic et al. [26] created a soft robot system to do indoor organic farming more effectively, and Montoya-Cavero et al. [23] studied the computer vision systems for harvesting robots.

2.10 Swarm Intelligence

Swarm intelligence focuses on the collective behavior of a decentralized or self-organized system. By working together as a group, the problems can be solved more reliably, securely, and efficiently than working alone. This is seen among social animals like birds, ants, and fish, but it can also be used in more complex situations, like smart and precision farming. The technological revolution of swarm intelligence has shown that it can be very useful in different areas of agriculture, such as annual crop planning, organization of agricultural products logistics, drones for smart farming, food operations, and plant leaf disease detection. Alternative solutions can be more cost-effective than the traditional methods, and can save time as well. Sethanan and Neungmatcha [31] proposed a particle swarm optimization-based routing solution for the sugarcane harvester robot while Karouani and Elgarej [18] proposed an efficient monitoring system that can optimize milk run logistics to reduce transportation costs.

3 CHALLENGES & OPPORTUNITIES

Big data and analytics in agriculture have been expanding rapidly as more computational power becomes available, resulting in more use cases, applications, and practices. Actual solutions to real-life problems are scarce though. Here we discuss about the implications and challenges that arise in data-driven agricultural practices as well as the research problems that need to be solved for the future of precision agriculture and smart farming systems.

3.1 Open Data & Open Access

The biggest challenge when training ML, DL, and AI models is to acquire large datasets. Data-driven models are data hungry by nature. This requires developing large public datasets containing various structured and unstructured data types such as texts, images, audios and videos, collected spatially and temporally. Data augmentation techniques, such as GAN and data wrapping, can be used to train the model more effectively but a more systematic solution to this issue is sought. For instance, GODAN (Global Open Data for Agriculture and Nutrition) promotes global efforts for open data and open access of agriculture and nutrition data. We need to encourage collaboration and cooperation among existing open data efforts, and bring stakeholders together to solve long-standing global problems in this regard.

3.2 Data Security & Privacy

Smart farming systems collect a lot of data from different interconnected sensors and devices. Data privacy is an important issue to

Figure 2: The challenges and opportunities for the future of data-driven precision agriculture and smart farming systems

the data owners, including farmers and producers in order to keep their agricultural operations safe, secure, and resilient. As innovations require constant communications, it is necessary to allow various stakeholders to share and access data while keeping them secure. For running businesses with different technologies and business models, data must be kept accurate and confidential, and it must also be authenticated to ensure that it is from the trustworthy source. This is especially difficult when it comes to agriculture because capital investments can often delay the growth of the smart farming industry. Moreover, a wide range of IoT devices used in the agricultural CPS could be vulnerable to cyberattacks and data breaches. As the environmental conditions can change, connected devices can also move around and affect security. To protect these systems, we need a way to store, process, and analyze data securely and reliably.

3.3 Adaptive & Novel Learning Models

A variety of technologies have been developed to improve agricultural productivity but there are still some areas where we do not have very good predictions as the agricultural environment changes constantly. Some of the factors that can affect the prediction accuracy include soil quality, rainfall, weather condition, etc. This calls for developing adaptive and self-learning models. Also, some DL models are fast and accurate while others are more accurate but take longer to compute. How to optimize the architecture of ANN is still a relatively unexplored research area. One way to tackle this is by using a hit and trail method, used in CNN. For smart agricultural systems, GAN has been used to solve diverse problems, including image enhancement, crop identification, early virus detection, plant disease detection, and salt tolerance [34]. However, it is a challenging task to select the optimal GAN model for a particular crop. To improve disease detection, researchers need to develop innovative algorithms to generate clearer images. This will help to improve the prediction accuracy while enhancing the model parsimony.

3.4 Hardware & Software Resources

For running effective ML, DL, and AI-based models, substantial investments must be made to install and maintain necessary hardware and software systems with adequate computational power such as high-performance computing (HPC) systems. For instance, IoT is supported by WSN but there are not enough sensors available to make smart farms work well [27]. Thus, it is still difficult to send accurate data from farms using wired or wireless networks. There are numerous IoT devices and several different IoT platforms to choose from, including ThingWorx, Amazon Web Services, and Sales force IoT Cloud. These platforms will make it easier for farmers to do business by providing them with useful data but the resources to integrate and compute a large amount of data are not sufficient to handle the recent growth in its usage. Also, edge devices are used to collect a large amount of data continuously, which is then sent to a cloud server. To manage the costs of smart agriculture, it is important to find ways to minimize the hardware costs of these devices. Poor internet connectivity in rural farmlands can also impose several challenges such as delays in responses, lost data, and slow data uploading speeds. It is imperative to invest and develop necessary infrastructures to support and advance the smart farming systems.

3.5 Communication & Training

When it comes to adopting new technology, farmers are not as advanced as researchers while researchers do not know all of the challenges that farmers are facing in the fields. Linking researchers with agricultural experts and producers together is the best way to learn about these challenges and to find ways to overcome them. Thus, constant and effective communications between farmers/producers and researchers are critical to advance the precision agriculture to the next level. Also, to help farmers understand and realize the benefits of using AI and robots in agricultural production systems, we need to provide technical training and educational support to farmers so that they can use the technology more effectively to increase the farm productivity.

3.6 Environmental Challenges

Extensive urbanization is continually threatening and reducing the agricultural land mass. Unpredictable environmental conditions due to the climate changes, etc. are also making it difficult to keep accurate track of soil nutrients, humidity, and temperature, all of which can affect plant growth and health, eventually the overall farm production levels. For running successful smart farms, we need to make the smart farming system more resilient and agile against these unexpected environmental changes or shocks. This requires systemic studies and thorough research in the uncertainty quantification of the environmental parameters.

4 CONCLUSION

Agricultural operation is changing, and new technology is helping to improve farming practices. Nevertheless, a lack of awareness about these advances could prevent the implementation of more sophisticated automation systems. There are a few studies that have looked at the impact of technology on agriculture, and they all concluded that this is a growing field with potential benefits for both farmers/producers and consumers. There are many different types of technology that could be used to help farmers but none of the surveys was able to provide a complete list of all the possible use cases of these technologies. For food security and sustainability, it is important to study this area in more detail to figure out the challenges, opportunities, and future directions of this smart agrotech; see Figure 2 for an illustrative summary.

REFERENCES

[1] Abbas, A., Jain, S., Gour, M., and Vankudothu, S., 2021. Tomato plant disease detection using transfer learning with C-GAN synthetic images. *Comput. Electron. Agric.* 187, 106279.

[2] Alonso, R.S., Sittón-Candanedo, I., García, Ó., Prieto, J., and Rodríguez-González, S., 2020. An intelligent edge-IoT platform for monitoring livestock and crops in a dairy farming scenario. *Ad Hoc Netw.* 98, 102047.

[3] Arsenovic, M., Karanovic, M., Sladojevic, S., Anderla, A., and Stefanovic, D., 2019. Solving current limitations of deep learning-based approaches for plant disease detection. *Symmetry* 11, 939.

[4] Bi, L. and Hu, G., 2020. Improving image-based plant disease classification with generative adversarial network under limited training set. *Front. Plant Sci.* 11, 583438.

[5] Bo, Y. and Wang, H., 2011. The application of cloud computing and the internet of things in agriculture and forestry. In *Proceedings of the International Joint Conference on Service Sciences.* IEEE, 168–172.

[6] Caro, M.P., Ali, M.S., Vecchio, M., and Giaffreda, R., 2018. Blockchain-based traceability in agri-food supply chain management: a practical implementation. In *Proceedings of the IoT Vertical and Topical Summit on Agriculture-Tuscany.* IEEE, 1–4.

[7] Elavarasan, D., Vincent, D.R., Sharma, V., Zomaya, A.Y., and Srinivasan, K., 2018. Forecasting yield by integrating agrarian factors and machine learning models: a survey. *Comput. Electron. Agric.* 155, 257–282.

[8] Förster, A., Behley, J., Behmann, J., and Roscher, R., 2019. Hyperspectral plant disease forecasting using generative adversarial networks. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium.* IEEE, 1793–1796.

[9] Fuentes, A., Yoon, S., Park, J., and Park, D.S., 2020. Deep learning-based hierarchical cattle behavior recognition with spatio-temporal information. *Comput. Electron. Agric.* 177, 105627.

[10] Gao, P., Zhang, Y., Zhang, L., Noguchi, R., and Ahamed, T., 2019. Development of a recognition system for spraying areas from unmanned aerial vehicles using a machine learning approach. *Sensors* 19, 313.

[11] Gautron, R., Maillard, O.A., Preux, P., Corbeels, M., and Sabbadin, R., 2022. Reinforcement learning for crop management support: review, prospects and challenges. *Comput. Electron. Agric.* 200, 107182.

[12] Ghafar, A.S.A., Hajjaj, S.S.H., Gsangaya, K.R., Sultan, M.T.H., Mail, M.F., and Hua, L.S., 2021. Design and development of a robot for spraying fertilizers and pesticides for agriculture. *Mater. Today Proc.* (in press).

[13] Gutiérrez, P., López-Granados, F., Peña-Barragán, J., Jurado-Expósito, M., and Hervás-Martínez, C., 2008. Logistic regression product-unit neural networks for mapping ridolfia segetum infestations in sunflower crop using multitemporal remote sensed data. *Comput. Electron. Agric.* 64, 293–306.

[14] Ip, R.H.L., Ang, L.M., Seng, K.P., Broster, J.C., and Pratley, J.E., 2018. Big data and machine learning for crop protection. *Comput. Electron. Agric.* 151, 376–383.

[15] Jamil, F., Ibrahim, M., Ullah, I., Kim, S., Kahng, H.K., and Kim, D.H., 2022. Optimal smart contract for autonomous greenhouse environment based on IoT blockchain network in agriculture. *Comput. Electron. Agric.* 192, 106573.

[16] Jiang, P., Chen, Y., Liu, B., He, D., and Liang, C., 2019. Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks. *IEEE Access* 7, 59069–59080.

[17] Karmas, A., Karantzalos, K., and Athanasiou, S., 2014. Online analysis of remote sensing data for agricultural applications. In *Proceedings of the European Conference on Free and Open-Source Software for Geospatial* (in press).

[18] Karouani, Y. and Elgarej, M., 2022. Milk-run collection monitoring system using the internet of things based on swarm intelligence. *Int. J. Inf. Syst. Supply Chain Manag.* 15, 1–17.

[19] Li, B., Lecourt, J., and Bishop, G., 2018. Advances in non-destructive early assessment of fruit ripeness towards defining optimal time of harvest and yield prediction: a review. *Plants* 7, 3.

[20] Liu, B., Tan, C., Li, S., He, J., and Wang, H., 2020. A data augmentation method based on generative adversarial networks for grape leaf disease identification. *IEEE Access* 8, 102188–102198.

[21] Love, D.C., Fry, J.P., Genello, L., Hill, E.S., Frederick, J.A., Li, X., and Semmens, K., 2014. An international survey of aquaponics practitioners. *PLoS One* 9, e102662.

[22] Luo, J., Zhao, C., Chen, Q., and Li, G., 2021. Using deep belief network to construct the agricultural information system based on internet of things. *J. Supercomput.* 1–27.

[23] Montoya-Cavero, L.E., Torres, R.D.L., Gomez-Espinosa, A., and Cabello, J.A.E., 2022. Vision systems for harvesting robots: produce detection and localization. *Comput. Electron. Agric.* 192, 106562.

[24] Osinga, S.A., Paudel, D., Mouzakitis, S.A., Athanasiadis, I.N., 2022. Big data in agriculture: between opportunity and solution. *Agricultural Systems* 195, 103298.

[25] Pham, X. and Stack, M., 2018. How data analytics is transforming agriculture. *Bus. Horiz.* 61, 125–133.

[26] Polic, M., Ivanovic, A., Maric, B., Arbanas, B., Tabak, J., and Orsag, M., 2021. Structured ecological cultivation with autonomous robots in indoor agriculture. In *Proceedings of the International Conference on Telecommunications.* IEEE, 189–195.

[27] Rahaman, M.M. and Azharuddin, M., 2022. Wireless sensor networks in agriculture through machine learning: a survey. *Comput. Electron. Agric.* 197, 106928.

[28] Rejeb, A., Abdollahi, A., Rejeb, K., and Treiblmaier, H., 2022. Drones in agriculture: a review and bibliometric analysis. *Comput. Electron. Agric.* 198, 107017.

[29] Salah, K., Nizamuddin, N., Jayaraman, R., and Omar, M., 2019. Blockchain-based soybean traceability in agricultural supply chain. *IEEE Access* 7, 73295–73305.

[30] Sawant, M., Urkude, R., and Jawale, S., 2016. Organized data and information for efficacious agriculture using PRIDE™ model. *Int. Food Agribusiness Manag. Rev.* 19, 115–130.

[31] Sethanan, K. and Neungmatcha, W., 2016. Multi-objective particle swarm optimization for mechanical harvester route planning of sugarcane field operations. *European J. Oper. Res.* 252, 969–984.

[32] Shaikh, T.A., Rasool, T., and Lone, F.R., 2022. Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. *Comput. Electron. Agric.* 198, 107119.

[33] Sharma, A., 2020. AI and robotics for reducing waste in the food supply chain: systematic literature review, theoretical framework and research agenda. *Working Paper.*

[34] Sharma, V., Tripathi, A.K, and Mittal, H., 2022. Technological revolutions in smart farming: current trends, challenges and future directions. *Comput. Electron. Agric.* 201, 107217.

[35] Skobelev, P., Laryukhin, V., Simonova, E., Goryanin, O., Yalovenko, V., and Yalovenko, O., 2020. Developing a smart cyber-physical system based on digital twins of plants. In *Proceedings of the World Conference on Smart Trends in Systems, Security and Sustainability.* 522–527.

[36] Song, H., Rawat, D.B., Jeschke, S., and Brecher, C., 2017. Agriculture cyber-physical systems. In *Intelligent Data-Centric Systems.* Academic Press, Boston, MA, 399–417.

[37] Tewari, V., Pareek, C., Lal, G., Dhruw, L., and Singh, N., 2020. Image processing based real-time variable-rate chemical spraying system for disease control in paddy crop. *Artif. Intell. Agric.* 4, 21–30.
[38] Trong, V.H., Yu, G.H., Vu, D.T., and Kim, J.Y., 2020. Late fusion of multimodal deep neural networks for weeds classification. *Comput. Electron. Agric.* 175, 105506.
[39] Wang, D., Vinson, R., Holmes, M., Seibel, G., Bechar, A., Nof, S., and Tao, Y., 2019. Early detection of tomato spotted wilt virus by hyperspectral imaging and outlier removal auxiliary classifier generative adversarial nets. *Sci. Rep.* 9, 1–14.
[40] Wen, J., Shi, Y., Zhou, X., and Xue, Y., 2020. Crop disease classification on inadequate low-resolution target images. *Sensors* 20, 4601.
[41] Whitmore, A., Agarwal, A., and Xu, L.D., 2015. The internet of things: a survey of topics and trends. *Inf. Syst. Front.* 17, 261–274.
[42] Yang, B. and Xu, Y., 2021. Applications of deep-learning approaches in horticultural research: a review. *Hortic. Res.* 8, 1–31.
[43] Zhang, J., Rao, Y., Man, C., Jiang, Z., and Li, S., 2021. Identification of cucumber leaf diseases using deep learning and small sample size for agricultural internet of things. *Int. J. Distrib. Sens. Netw.* 17, 15501477211007407.
[44] Zhao, Y., Chen, Z., Gao, X., Song, W., Xiong, Q., Hu, J., and Zhang, Z., 2021. Plant disease detection using generated leaves based on DoubleGAN. *IEEE Trans. Comput. Biol. Bioinform.* 19, 1817–1826.