A Comprehensive Review on the Use of Artificial Intelligence, Internet of Things, Sensors, and Green Energy in Non-Invasive Agricultural Techniques

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Abstract—**Feeding a burgeoning global population amid climate change and dwindling resources presents a profound challenge for agriculture. This paper examines "smart agriculture" (Agriculture 4.0) as a pivotal solution, integrating technologies like IoT, AI, and robotics to cultivate data-driven, efficient, and sustainable farming. We emphasize the growing effectiveness of multi-modal data fusion—combining diverse sensor inputs—for improved pest detection, water management, and yield prediction. A critical shift towards decentralized edge intelligence is also explored, facilitating real-time, on-farm decisions and overcoming connectivity hurdles. While acknowledging that successful implementations are highly context-specific and that synthetic data can address scarcity, we also confront persistent obstacles: high adoption costs, the digital divide, unreliable rural connectivity, and cybersecurity risks. Ultimately, realizing smart agriculture's full potential—a more resilient and productive global food system—requires sustained investment in affordable sensors, robust and explainable AI, and autonomous robotics to translate data insights into actionable field-level strategies.**

Index Terms—**Smart Agriculture, Non-Invasive Agriculture, Artificial Intelligence, Internet of Things, Sensors, Green Energy, Machine Learning, Robotics, Precision Agriculture**

I. Introduction

The worldwide agro-economy is at a crossroad and facing a huge challenge to feed the world population expected to reach nearly 10 billion by 2050 [1] [2]. However, this need must be fulfilled in the face of strong headwinds, including the impact of the climate change, the reductions in natural resources, and an increased demand for environmental sustainability [3] [4]. In reaction, it has resulted in a technological revolution in the agricultural field, leading to farming processes shaping into "smart agriculture" or "Agriculture 4.0" [1]. That new model requires the use new technologies such as IoT, AI, ML and robotics to build data-driven, automated and sustainable farming system [5] [6]. Using real-time data from various sources that range from sensors in fields to aerial drones, smart agriculture intends to optimize the use of resources, in- crease crop yield, and reduce the environmental impact of cultivating crops, thus paving the way for a precision and sustainable agriculture revolution [1]. This review synthesizes the results of a number of recent studies to give a broad overview of these game-changing technologies and their applications in all areas of agriculture.

II. Background: The Emergence of Smart-Farming and Precision-Agriculture

Precision agriculture and smart farming are technological advancements in agriculture which are required to cope with the ever-increasing food needs of expanding global population while dealing with uncertainties that prevail in the form of climate, resource availability, and loss of agricultural lands [1]. Of particular note, climate change is causing significant impacts on water resource availability and crop growth shortening the growing season, and effective management becomes critical [2]. The general expectation among industry analysts is that the pervasive adoption of new technologies like cloud computing, Internet of Things (IoT), robotics and Artificial Intelligence (AI) will revolutionize agriculture, albeit while creating obstacles that help to undermine existing farming practices [3] [6]. Smart farming can optimize resources such as water and fertilizers [4] and improve production while preserving the environment [1]. This method helps the agriculture evolved from the existing farming practices to a more standard, precise, and efficient practice, which is called "Agriculture 4.0" that uses digital technology to smart up farming and maximize output [1]. A key aspect of smart farming leverages technologies to collect massive amounts of data for decision making [4]; contributing to a better yield of crop, better management of resources, and sustainability of the environment [5]. By modernizing classic farming principles, this kind of technology makes farm work resemble a smart and automated system [1].

III. Key Technologies in Non-Invasive Agricultural Techniques

Modern agriculture is rapidly evolving, with non-invasive techniques becoming central to sustainable and efficient farming practices. These approaches heavily rely on advanced technologies to monitor, analyze, and manage crop health and environmental conditions without disturbing the plants or soil. Figure 1 demonstrate the main technologies used in the field of smart farming system.

A. The Role of the Internet of Things (IoT)

One of the fundamental technologies for smart agriculture is the (IoT) which establishes a network of interconnected smart sensors which interact over the internet to monitor, control and visualize different farm activities in real time [1] [2] [6] [7] [8]. This major platform of the Industry 4.0 revolution is impacting many aspects of everyday lives, and is now on track to drive the agriculture industry forward [5] [9]. The architecture of such systems usually consists of a sensor input layer, a connectivity layer, and a data

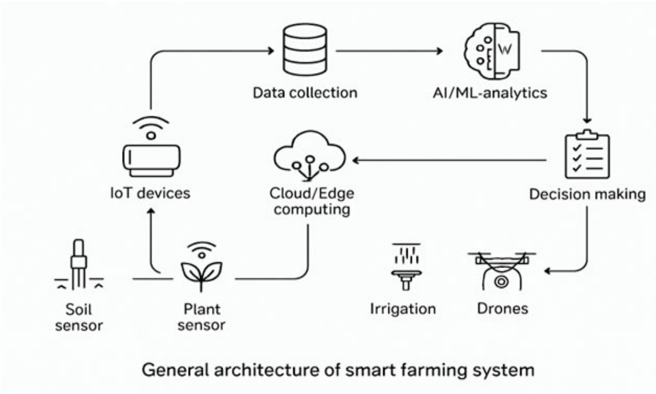

Fig. 1. General Architecture of a Smart Farming System

processing layer [10] [11]. (diverse sensors scattered over fields which measures the important parameters such as soil moisture, temperature, humidity, the pH of soil, concentration of soil nutrients including N, P, K [12] [13] [14]. This data is transmitted by the connectivity layer over wireless communication protocols. Such technologies as Wi-Fi and mobile (GSM/4G) are wide present, but for remote areas with poor infrastructure, Low Power Wide-Area Network (LPWAN) standards, such as of LoRaWAN, are more suitable [15] [16] [17]. LoRaWAN allows long-range (up to 15 km), low-power, secure data transfer and is well suited to connect battery-powered sensor nodes distributed in large farms [15] [18]. In some more sophisticated systems, UAVs are employed as mobile gateways and they fly over the rural areas to collect data from ground nodes that do not have terrestrial internet [19]. Other systems adopt routing algorithms following the IEEE 802.15.4 standard for efficient data routing from sensors to UAVs [19]. This data is collected and forwarded to a centralized platform, typically a cloud server by platforms such as ThingSpeak, where it is processed, organized on dashboards for visualization, and analyzed for triggering automatic actions and making decisions [1] [12].

B. The Role of Artificial Intelligence (AI) and Machine Learning (ML)

Artificial I ntelligence (AI), t he s cience a nd engineering of making intelligent machines, is a key driver in the shift towards smart agriculture [1] [20]. AI technologies enable machines to simulate human intelligence, allowing for learning, problem-solving, and wise decision-making in agricultural contexts [6] [20] [21]. In smart farming, AI is used for a wide range of applications, including pest and disease detection, yield prediction, weed management, and agricultural robotics [1] [5] [6] [22]. AI-based algorithmic models analyze the data collected by IoT sensors to provide actionable insights [2]. For example, AI can analyze images of plant leaves to diagnose diseases [22] [23] or use sound data from IoT devices to detect the presence of pests like the Red Palm Weevil [24] [25]. Some advanced systems utilize an Autonomous Cycle of Data Analysis Tasks (ACODAT), which integrates multiple AI techniques. For example, a cycle might use XGBoost for pest classification, a fuzzy system for yield diagnosis, and genetic algorithms for prescribing the best management strategies for a given crop [4] [25]. Furthermore, Generative AI is being used to create realistic, synthetic data to augment real-world datasets [5] [26]. This is particularly useful for training more robust and accurate predictive models for crop yield forecasting, especially when real data is limited [5] [27]. The ultimate goal of integrating AI into agriculture is to create more autonomous, efficient, a nd s ustainable f arming s ystems that can adapt to changing conditions and improve productivity [21] [27]. Machine Learning (ML), a field within AI, provides the algorithms that allow systems to learn from data and make predictions or decisions without being explicitly programmed [13] [27]. ML is invaluable for analyzing the complex and high-dimensional data generated in modern agriculture [5] [28]. Various ML models are used for specific t asks. For predicting crop suitability, models like Decision Trees (DT), Random Forests (RF), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) are used to analyze climate, environmental, and soil factors [13] [28]. For more complex tasks like soil nutrient prediction from spectral data, models such as Partial Least Squares Regression (PLSR) and Support Vector Machine Regression (SVMR) have proven effective, yielding high accuracy in generating soil suitability maps [24] [29]. Deep learning, a more advanced form of ML using complex neural networks, is particularly effective at handling large datasets and identifying intricate patterns [5] [29]. For instance, Convolutional Neural Networks (CNNs) are widely used for image-based tasks such as identifying pests on tomato leaves [30] [31] or detecting diseases in palm trees [24] [32]. Advanced architectures like Vision Transformers are also being used to classify rice leaf diseases from images taken in uncontrolled field c onditions (“in the wild”) [33] [34]. Another innovative application is the use of ML models as “virtual sensors,” which can predict sensor values in locations where no physical hardware is deployed, offering a cost-effective and scalable alternative to dense sensor networks [34] [35]. The Light Gradient Boosting Machine (LGBM) model, for example, has proven highly accurate for this purpose [35] [34]. By processing historical and real-time data, ML algorithms provide accurate predictions that support data-driven decision-making for better crop management and resource allocation [13] [27].

C. The Role of Sensor Technologies

Sensor technologies form the backbone of smart agriculture systems, enabling non-invasive monitoring by providing critical data on environmental conditions, plant health, and soil properties. Fig. 2 shows how sensors are used in obtaining different information related to agriculture.

These sensors offer farmers a real-time flow of information, allowing them to make more informed and timely decisions. Sensors used in agriculture cover a wide range, primarily including:

- **Soil Sensors:** Measure soil moisture, temperature, pH levels, and nutrient (N, P, K) concentrations. This data is used to optimize irrigation and fertilization programs, thereby preventing resource waste and increasing efficiency [12] [13] [34]. For example, precision irrigation systems adjust water distribution based on data from soil moisture sensors, significantly improving water use efficiency [34].
- **Plant Sensors:** Monitor plant health, growth, and stress levels. Spectral sensors analyze light reflected from plant leaves to provide information on chlorophyll content, disease presence, and nutrient deficiencies [36] [37].

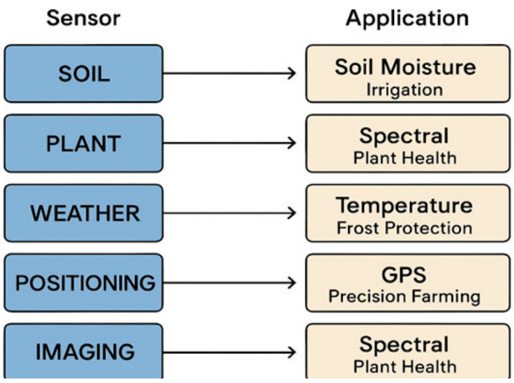

Fig. 2. Various Sensor Types used to implement smart non-invasive agriculture

Thermal cameras can measure plant temperature to detect water stress or disease symptoms [37]. Acoustic sensors can identify the presence of pests (e.g., Red Palm Weevil) through sound waves [24] [25].

- **Weather Sensors:** Collect atmospheric data such as air temperature, humidity, wind speed and direction, precipitation, and solar radiation. This information is vital for planning agricultural activities like planting, harvesting, and spraying [2] [37].
- **Positioning Sensors (GPS/GNSS):** Provide precise positioning in agricultural fields. This allows for accurate guidance of tractors and other agricultural machinery, precise planting and fertilization, and the creation of yield maps [5] [38].
- **Imaging Sensors (Cameras and Multispectral/Hyperspectral Sensors):** Mounted on UAVs and satellites, these sensors capture high-resolution images of large areas. These images are used for detailed analyses of plant density, growth rate, disease spread, and weed detection [36] [30] [39] [40]. Multispectral images, in particular, can reveal plant health issues invisible to the human eye [41].

The integration and analysis of sensor data form the foundation of smart agriculture. This data, combined with AI and ML algorithms, provides customized recommendations to farmers and enables autonomous systems (robots, UAVs) to perform precise interventions in the field. Non-invasive sensors offer a more sustainable and efficient approach compared to traditional methods by allowing continuous monitoring without harming plants or soil.

D. The Role of Green Energy Solutions

Green energy solutions are important to contribute to the sustainability goals of smart agriculture systems and to reduce their environmental impact. Figure 3 shows how green energy integrates into agriculture. It is not unusual for greenhouse gas emissions to occur as a result of fossil fuel use on traditional farm enterprises. The reliance on green energy helps to alleviate this dependency and is a more environmental-friendly and efficient form of agricultural production.

There are major methodsof applying green energy to non-invasive agricultural methods:

- **Solar Power:** take advantage of the sun by using solar panel to charge the inbuilt battery during the day and

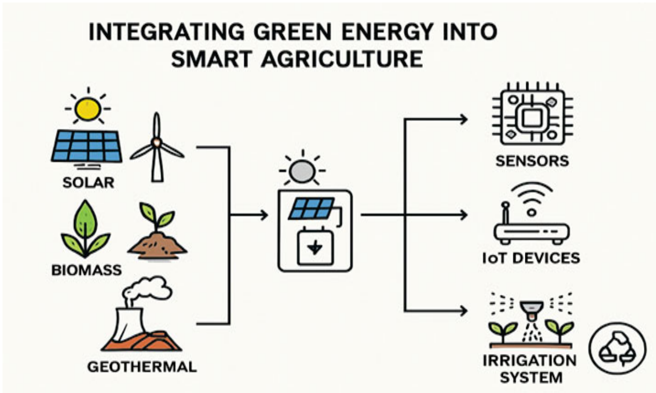

Fig. 3. The integration of the green energy to the agriculture

operate at night for sensors, iot devices, irrigation pumps and any other electrical equipment, both in the case of Solar energy to provide clean and Renewable energy in Agriculture. In particular for off-grid or remote rural areas, is solar power to drive autonomous farming. UAV charging stations or sensor nodes solar-powered guarantee a constant operation and data collection [21] [42] [43].

- Wind – Small wind turbines can supplement an on-farm energy system and may be appropriate for agricultural operations in high-wind areas. These turbines are capable of providing the required energy to farm buildings, warehouses or irrigation systems [44].
- **Biomass Energy:** Agricultural residue (plant residue, animal manure) can be utilised by biomass energy. The biogas plants can convert methane gas out of this waste into electric power and heat. This would allow for better waste disposal while enhancing the energy autonomy of the farms [45].
- **Geothermal Energy:** Geothermal energy may be used for purposes such as the heating of greenhouses, or water heating. It is an ideal way to save energy and reduce carbon release, especially based on controlled environment agriculture [45].

Adopting green energy innovation in smart agriculture systems also serves to protect the environment and scale up farmers' profits, as their energy costs are nipped in the bud. This is essential for long-term sustainability of agriculture and makes the agricultural sector more robust and self-reliant [45].

IV. Analysis of Provided Papers and Their Usefulness in Agriculture

The papers, which were provided in this paper, present a broad range of applications in smart agriculture, using technologies including AI, IoT, robotics, and so on, to solve different problems. They can also be grouped according to their main use in agriculture.

A. Crop Observation, Diseases Recognition and Pest Forecasting

This is the majority class for the provided papers, depicting the great significance of such challenges to observe the health of crops and predict yields with high levels of accuracies for them to be realized for food production and to employ sustainable practices. EdgePlantNet, a light-weight two-branched Convolutional Neural Network (CNN) is presented which is capable of real-time plant disease detection on resource-limited edge devices such as a Raspberry Pi [23][45]. Its novelty is based on an advanced spatial attention mechanism, which leverages the processed original leaf im-ages and segmented leaf images to achieve high accuracy and require for fewer number of data samples.

Furthermore, some studies proposes an IoT and deep learning based sustainable system for tomato pest management. This system uses a camera and moisture sensor to detect humidity and uses ten different learning models for observation of the conditions where dense net 201 delivers the highest accuracy of 94% in classifying seven pests [46] [47]. The work on Red Palm Weevil (RPW) inspection proposes a novel solution that aggregates both audio and visual data (UAV based images) collected by IoT devices for identifying and mapping the presence of RPW infestation in palm trees [24] [47]. It aims at classifying the health of the tree from weevil sound, while detecting trees and reaching high accuracy for 26 infected plants, using deep learning models (InceptionV3 and YOLOv8) that classify the health of the tree based on sound weevil and detect the trees from images. The study which developed predictive model on crop growth rate of Amaranthus Viridis in a hydroponic setup compares a total of twelve machine learning models and finds XGBoost to be the best among the compared models to automate the crop prediction process [35] [48]. The study on the AIoT oriented soil nutrient analysis system suggests farmers using an Android motioned app with crop suggestions from soil real-time parameters (N, P, K, pH) along with the environmental parameters [13]. It compares five machine learning algorithms and it is observed that Decision Tree with AdaBoost provides better (98% accuracy) crop recommendation results. A deep learning approach to crop monitoring in greenhouses is presented in [49] [50] where IoT sensor data and different deep learning models are applied for long-term monitoring as well as for autonomous regulation of the greenhouse, so that resource usage can be optimized and productivity increased. The study regarding precision of the rice grain moisture content (GMC) that makes use of a UAV with multi-spectral sensor for the development of a nondestructive method for estimation of GMC was conducted by [36] [50]. With the combination of FC, the significant improvement of FVS systems and the machine-learning models (RF, SVM, MLP), the system can achieve high accuracy for prediction compared to pre-vious works, which helps the farmer to efficiently dry the agriculture output as well as to increase the crop quality. Another paper deals with personalized crop-specific feature formulation by means of genetic programming (GP) for early and in season crop mapping, which is a hard problem brought about by limited image access [30]. The GP approach also designs features automatically which amplify slight spectral differences between crops that outweigh traditional spectral features and those vegetation indices particularly in early-season mapping. The ICM study proposes an Autonomous Cycle of Data Analysis Tasks (ACODAT) with integration of several AI methods [4] [51]. It employs XGBoost to classify insects, fuzzy decision to predict and diagnose cotton yield, and genetic algorithm to prescribe the best decision choices and achieving high accuracy in its various tasks.

A vision transformer (VT)-based method is introduced for "in the wild" (i.e., complex, uncontrolled field) image-based classification of rice leaf diseases [33] [51]. This approach is robust against class imbalance and outperforms some other deep learning frameworks . Also, an AI-based Generative sys-tem involving deep learning (ANN, GAN, YOLO) combined with GPS and GIS technologies for smart precision farming, which allows to monitor the crops and predict the yields with a good level of accuracy [5] [52].

In the context of a study about plant health monitoring, a smart irrigation system is proposed based on a bubble identification method for assessing vascular health of plants by identifying embolisms as early warnings for health problems [53].

B. Automation, Robotics, and Advanced Decision System

These papers focus on the integration of robotics and automated systems to improve the efficiency, sustainability, and decision-making processes in farming operations.

The work on Advanced Robotic Decision System presents a Pliant Decision System (PDS) for Farming Robots (FRs) [21] [54]. It adopts a two-layer-deep RNN model to lead to syncrhonized multi-opeartional time-sensitive agricultural activities, and verifies the sustainability forumlation and enhances task complete-proness and syncrhonization in robotic tasks.

- A LoRa-based system with periodic UAV transmissions: A different communication scheme consistent with the literature results is presented in a work with scheduled UAVs communication for rural areas without internet coverage [55]. A fixed-wing UAV equipped with an on-board LoRa gateway traverses a predetermined route for gathering data from periodic transmissions of ground-based IoT nodes, after which the collected data are then extracted in an energy-efficient manner.
- Botta et al.'s review paper dealing with smart applications in agriculture, describe the use of automated vehicles, drones and robotic machinery for activities such as sowing, spraying or harvesting, and highlights its application for achieving precision agriculture [56].
- An article presenting a robot system for automated picking of mushrooms that employs computer vision and a 6-degrees of freedom robotic arm to identify and pick ripe mushrooms, thereby, achieving higher efficiency and saving human labour power [57]
- An autonomous navigation for robotic agriculture research employing advanced sensor fusion and path planning algorithms, aiming at enabling robots to work in a complex farm environments independently, with higher precision and less human participation [58]
- A study of the use of drones for precision spraying of grapevines is an example of UAVs to more efficiently use pesticides and fertilisers, leading to less chemicals being applied and contributing to reduced pesticide use and chemicals on the environment [59] [60].
- The work on intelligent decision support system for irrigation management combines real-time sensor level information with meteorological predictions and crop models to obtain the optimal irrigation scheduling, optimizing water usage efficiency and crop yield [61].
- Studies of a robot system for high-throughput phenotyping have focused on automatic plant phenotyping using plant imaging and machine learning for phenotypic analysis to support breeding and crop improvement programs [62].

Despite the great achievements already made in the field of smart agriculture technology, there are various challenges that are still preventing this technology from being widely implemented and reaching its full potential. Such challenges and future research directions are:

- High Cost of Implementation: The cost of adopting smart agriculture systems is high, particularly for smallholder farmers, in terms of its initial setup cost. Equipment such as sensors, IOT devices, software based on AI and robotics demand considerable investments [63]. Further research should be directed at finding more economic and large-scale alternatives. Both the costs of open-source hardware and software can be significantly lower.
- Digital Divide and Poor Technical Knowledge: Farmers in Third World countries and rural areas may not have much access to technology and technical knowledge. This all slows the rollout of smart agriculture technology. Training, user friendly applications and support in local languages are necessary to fill this gap. Furthermore, there is a need to widely promote successful pilot projects to build farmers' confidence in adopting technology [64].
- Inconsistent Rural Connectivity: Both IoT devices and cloud-based AI require good internet connection to reliably and quickly function. Yet this is not available in much of rural. 5G and satellite Internet services (e.g., Starlink) have the potential of solving this problem. Another approach to decrease dependence from connectivity can be approximated by edge computing solutions which allow data processing at home [64].
- Data Privacy and Cybersecurity: Smart agriculture systems copiously gather confidential and sensitive information (crop data, soil analyses, farm operations). We certainly need to secure this data against unauthorized access and abuse. It is essential to build robust encryption, safe data storage and ethical use-of-data practices. Data integrity and transparency as a potential solution to ensure data integrity and transparency, blockchain technology may be adopted [5].
- Data Integration and Standardization: Absence of data integration and interoperability between sensors and platforms provided by different vendors complicates smart farming systems. Interoperable data formats and open APIs will enable the various systems to communicate freely with one another and lead to the creation of better integrated, more efficient systems [65].

- Growth of Autonomous Robotics and Automation: Robotics and automation for agriculture, if performed by robots, could help to reduce human labor associated with planting, harvesting, weeding and spraying. Yet, these robots still require additional research and development to enable them to function in completely autonomous way in miniaturing and dynamic agricultural settings. In particular, it is an issue to realize the robots which can walk in irregular terrains and produce the motion in an exact work position [1].
- Green Energy Integration: Fulfilling the energy demand of smart agriculture only with renewables is a must for achieving environmental sustainability though achieving this objective remains a challenge. In addition, hybrid energy systems (such as solar and wind), energy storage, and energy-efficiency scheduling are promising research focused for the future in this area [6].

Addressing these challenges is critical for smart agriculture to achieve its full potential in securing global food supply and promoting environmental sustainability. Interdisciplinary cooperation, theory and practice cooperation, and innovative research strategies will be necessary in order to reach these goals. Non-invasive cultivation methods are also expected to become well-known in the integrated system of future food production and are hoped to become bright prospects in the sustainable agricultural future.

V. Conclusion

This review article discusses the evolution of Artificial Intelligence (AI), Internet of Things (IoT), sensors system, and green energy concepts in the perspective of non-invasive agriculture practices in breadth. This paradigm, commonly termed smart agriculture of Agriculture 4.0, is driven by the pressures of worldwide challenges and demands like food security, resource efficiency, and environmental sustainability [1] [6] [63]. Real-time collection of data using IoT sensors, AI/ML data analysis and robotic automation are at the base of next-generation farming. Although some previous studies compared the performance of single-modal with multi-mode data fusion techniques and reported more accurate and robust results in disease detection, water stress assessment and yield prediction [4] [13] [21] [36]. A move in architecture from centralized cloud computing to edge computing has been recognized to be necessary to speed up on-farm decision making and to cope with connectivity constraints.

From the literature review conducted, smart agriculture instruments have been verified u seful i n t he fi eld of crop system monitoring, disease and pest detection, automation, and advanced decision support systems. Nevertheless, there are still some obstacles such as high cost of deployment, the digital divide, unstable rural connections, and threat of cyber security [5] [63] [64]. Concentrated research is required in affordable sensors, securer and explainable AI models and autonomous robots to address these challenges. The application of green energy solutions has the potential to alleviate environmental impacts of agricultural activities as well as promoting energy independence [1] [2] [3] [4] [6] [65].

In summary, smart agriculture powered by digital tools holds strong promise in boosting the global food system that is more reliable and productive. To unlock the promise of these technologies also takes innovation, cross-cutting cooperation and the creation of products that respond to farmer needs. Non-contact farming methods will be the key to the future food production and will bring a great hope for our agriculture future.

References

[1] M. E. Alaoui, K. E. Amraoui, L. Masmoudi, A. Ettouhami, and M. Rouchdi, "Unleashing the potential of iot, artificial intelligence, and uavs in contemporary agriculture: A comprehensive review," *Journal of Terramechanics*, vol. 115, p. 100986, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0022489824000284

[2] M.-D. Yang, Y.-C. Hsu, W.-C. Tseng, H.-H. Tseng, and M.-H. Lai, "Precision assessment of rice grain moisture content using uav multispectral imagery and machine learning," *Computers and Electronics in Agriculture*, vol. 230, p. 109813, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169924012043

[3] M. Milovanović, J. Pejić, and P. Pejić, "Advanced sensors for noninvasive bee colony inspection," *Computers and Electronics in Agriculture*, vol. 231, p. 109945, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169925000511

[4] J. Yao, Y. Gong, Z. Xia, P. Nie, H. Xu, H. Zhang, Y. Chen, X. Li, Z. Li, and Y. Li, "Facility of tomato plant organ segmentation and phenotypic trait extraction via deep learning," *Computers and Electronics in Agriculture*, vol. 231, p. 109957, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169925000638

[5] J. Zhang, Z. Fu, K. Zhang, J. Li, Q. Cao, Y. Tian, Y. Zhu, W. Cao, and X. Liu, "Optimizing rice in-season nitrogen topdressing by coupling experimental and modeling data with machine learning algorithms," *Computers and Electronics in Agriculture*, vol. 209, p. 107858, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169923002466

[6] C. Kang, G. Diverres, M. Karkee, Q. Zhang, and M. Keller, "Decision-support system for precision regulated deficit irrigation management for wine grapes," *Computers and Electronics in Agriculture*, vol. 208, p. 107777, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169923001655

[7] Z. He, Y. Bao, Q. Yu, P. Lu, Y. He, and Y. Liu, "Dynamic path planning method for headland turning of unmanned agricultural vehicles," *Computers and Electronics in Agriculture*, vol. 206, p. 107699, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S016816992300087X

[8] W. Shi, B. Dai, W. Shen, Y. Sun, K. Zhao, and Y. Zhang, "Automatic estimation of dairy cow body condition score based on attention-guided 3d point cloud feature extraction," *Computers and Electronics in Agriculture*, vol. 206, p. 107666, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169923000546

[9] R. Amen, J. Hameed, G. Albashar, H. W. Kamran, M. U. Hassan Shah, M. K. U. Zaman, A. Mukhtar, S. Saqib, S. I. Ch, M. Ibrahim, S. Ullah, A. G. Al-Sehemi, S. R. Ahmad, J. J. Klemeš, A. Bokhari, and S. Asif, "Modelling the higher heating value of municipal solid waste for assessment of waste-to-energy potential: A sustainable case study," *Journal of Cleaner Production*, vol. 287, p. 125575, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959652620356213

[10] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of things: A survey on enabling technologies, protocols, and applications," *IEEE Communications Surveys & Tutorials*, vol. 17, no. 4, pp. 2347–2376, 2015.

[11] Z. Ouyang, J. Tian, X. Yan, and H. Shen, "Effects of different concentrations of dissolved oxygen on the growth, photosynthesis, yield and quality of greenhouse tomatoes and changes in soil microorganisms," *Agricultural Water Management*, vol. 245, p. 106579, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378377420321260

[12] A. Kahmann, M. J. Anzanello, M. C. A. Marcelo, and D. Pozebon, "Near infrared spectroscopy and element concentration analysis for assessing yerba mate (ilex paraguariensis) samples according to the country of origin," *Computers and Electronics in Agriculture*, vol. 140, pp. 348–360, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169916309322

[13] Y. Su, H. Si, J. Chen, and G. Wu, "Promoting the sustainable development of the recycling market of construction and demolition waste: A stakeholder game perspective," *Journal of Cleaner Production*, vol. 277, p. 122281, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959652620323283

[14] Y.-S. Kim, M. A. A. Siddique, W.-S. Kim, Y.-J. Kim, S.-D. Lee, D.-K. Lee, S.-J. Hwang, J.-S. Nam, S.-U. Park, and R.-G. Lim, "Dem simulation for draft force prediction of moldboard plow according to the tillage depth in cohesive soil," *Computers and Electronics in Agriculture*, vol. 189, p. 106368, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169921003859

[15] G. T. Marangwanda, D. M. Madyira, and T. O. Babarinde, "Coal combustion models: An overview," *Journal of Physics: Conference Series*, vol. 1378, no. 3, p. 032070, dec 2019. [Online]. Available: https://dx.doi.org/10.1088/1742-6596/1378/3/032070

[16] X. Shi, X. Li, C. Guo, P. Feng, and K. Hu, "Modeling ammonia volatilization following urea and controlled-release urea application to paddy fields," *Computers and Electronics in Agriculture*, vol. 196, p. 106888, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169922002058

[17] Y. Wang, X. Yu, D. An, and Y. Wei, "Underwater image enhancement and marine snow removal for fishery based on integrated dual-channel neural network," *Computers and Electronics in Agriculture*, vol. 186, p. 106182, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S016816992100199X

[18] J. Zhou, J. Li, C. Wang, H. Wu, C. Zhao, and Q. Wang, "A vegetable disease recognition model for complex background based on region proposal and progressive learning," *Computers and Electronics in Agriculture*, vol. 184, p. 106101, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169921001198

[19] P. Grabowski, L. Schmitt Olabisi, J. Adebiyi, K. Waldman, R. Richardson, L. Rusinamhodzi, and S. Snapp, "Assessing adoption potential in a risky environment: The case of perennial pigeonpea," *Agricultural Systems*, vol. 171, pp. 89–99, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0308521X18307479

[20] J. R. Millan-Almaraz, I. Torres-Pacheco, C. Duarte-Galvan, R. G. Guevara-Gonzalez, L. M. Contreras-Medina, R. de Jesus Romero-Troncoso, and J. R. Rivera-Guillen, "Fpga-based wireless smart sensor for real-time photosynthesis monitoring," *Computers and Electronics in Agriculture*, vol. 95, pp. 58–69, 2013. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169913000835

[21] J. A. Jose, C. Sathish Kumar, and S. Sureshkumar, "A deep multi-resolution approach using learned complex wavelet transform for tuna classification," *J ournal o f K ing Saud University - Computer and Information Sciences*, vol. 34, no. 8, Part B, pp. 6208–6216, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1319157821000689

[22] Y. Di, J. Dong, F. Zhu, and P. Fu, "A robust but straightforward phenology-based ginger mapping algorithm by using unique phenology features, and time-series sentinel-2 images," *Computers and Electronics in Agriculture*, vol. 198, p. 107066, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169922003830

[23] Y. Liu, X. Huang, Q. Yang, and Y. Cao, "The turning point between urban vegetation and artificial s urfaces f or their competitive effect on land surface temperature," *Journal of Cleaner Production*, vol. 292, p. 126034, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959652621002547

[24] J. Gorle, B. Terjesen, and S. Summerfelt, "Hydrodynamics of octagonal culture tanks with cornell-type dual-drain system," *Computers and Electronics in Agriculture*, vol. 151, pp. 354–364, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169918302187

[25] M. Zhang, H. Feng, J. Tomka, M. Polovka, R. Ma, and X. Zhang, "Predicting of mutton sheep stress coupled with multi-environment sensing and supervised learning network in the transportation process," *Computers and Electronics in Agriculture*, vol. 190, p. 106422, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169921004397

[26] L. Meng, H. Liu, X. Zhang, C. Ren, S. Ustin, Z. Qiu, M. Xu, and D. Guo, "Assessment of the effectiveness of spatiotemporal fusion of multi-source satellite images for cotton yield estimation," *Computers and Electronics in Agriculture*, vol. 162, pp. 44–52, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S016816991831651X

[27] Y. Domun, L. J. Pedersen, D. White, O. Adeyemi, and T. Norton, "Learning patterns from time-series data to discriminate predictions of tail-biting, fouling and diarrhoea in pigs," Computers and Electronics in Agriculture, vol. 163, p. 104878, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169918313383

[28] T. Miao, C. Zhu, T. Xu, T. Yang, N. Li, Y. Zhou, and H. Deng, "Automatic stem-leaf segmentation of maize shoots using three-dimensional point cloud," Computers and Electronic in Agriculture, vol. 187, p. 106310, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169921003276

[29] L. Parsons and R. Ross, "A computer-vision approach to bait level estimation in rodent bait stations," Computers and Electronics in Agriculture, vol. 172, p. 105340, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169919320447

[30] X. Xu, H. Wang, W. Li, and M. Wang, "Distributed output tracking via event-triggered control for nonlinear multi-agent systems," Journal of King Saud University - Computer and Information Sciences, vol. 34, no. 10, Part B, pp. 9173–9183, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1319157822003226

[31] W. Jia, Y. Tian, R. Luo, Z. Zhang, J. Lian, and Y. Zheng, "Detection and segmentation of overlapped fruits based on optimized mask r-cnn application in apple harvesting robot," Computers and Electronics in Agriculture, vol. 172, p. 105380, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169919326274

[32] S. Murugeswari, K. Murugan, S. Rajathi, and M. Santhana Kumar, "Monitoring body temperature of cattle using an innovative infrared photodiode thermometer," *Computers and Electronics in Agriculture*, vol. 198, p. 107120, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169922004379

[33] P. Cannavo, L. Vidal-Beaudet, and C. Grosbellet, "Prediction of long-term sustainability of constructed urban soil: impact of high amounts of organic matter on soil physical properties and water transfer," *Soil Use and Management*, vol. 30, no. 2, pp. 272–284, 2014. [Online]. Available: https://bsssjournals.onlinelibrary.wiley.com/doi/abs/10.1111/sum.12112

[34] L. Fu, F. Wu, X. Zou, Y. Jiang, J. Lin, Z. Yang, and J. Duan, "Fast detection of banana bunches and stalks in the natural environment based on deep learning," *Computers and Electronics in Agriculture*, vol. 194, p. 106800, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S016816992200117X

[35] N. Zhang, M. Wang, and N. Wang, "Precision agriculture—a worldwide overview," *Computers and Electronics in Agriculture*, vol. 36, no. 2, pp. 113–132, 2002. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169902000960

[36] Y. Zhang, H. Long, L. Ma, S. Tu, Y. Li, and D. Ge, "Analysis of rural economic restructuring driven by e-commerce based on the space of flows: The case of xiaying village in central china," *Journal of Rural Studies*, vol. 93, pp. 196–209, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0743016718302109

[37] X. He, D. Zhang, L. Yang, T. Cui, Y. Ding, and X. Zhong, "Design and experiment of a gps-based turn compensation system for improving the seeding uniformity of maize planter," *Computers and Electronics in Agriculture*, vol. 187, p. 106250, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169921002672

[38] Y. Ampatzidis, V. Partel, B. Meyering, and U. Albrecht,

"Citrus rootstock evaluation utilizing uav-based remote sensing and artificial intelligence," *Computers and Electronics in Agriculture*, vol. 164, p. 104900, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169919311123

[39] C. Juhász, B. Gálya, E. Kovács, A. Nagy, J. Tamás, and L. Huzsvai, "Seasonal predictability of weather and crop yield in regions of central european continental climate," *Computers and Electronics in Agriculture*, vol. 173, p. 105400, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169919312104

[40] H. Zhang, B. He, J. Xing, and M. Lu, "Spatial and temporal patterns of rice planthopper populations in south and southwest china," *Computers and Electronics in Agriculture*, vol. 194, p. 106750, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169922000679

[41] S. Zhang, W. Ren, B. Xie, Z. Luo, C. Wen, Z. Chen, Z. Zhu, and T. Li, "A combined control method of traction and ballast for an electric tractor in ploughing based on load transfer," *Computers and Electronics in Agriculture*, vol. 207, p. 107750, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169923001382

[42] J. Chen, J. Wu, Z. Wang, H. Qiang, G. Cai, C. Tan, and C. Zhao, "Detecting ripe fruits under natural occlusion and illumination conditions," *Computers and Electronics in Agriculture*, vol. 190, p. 106450, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169921004671

[43] M. Swoish, J. F. Da Cunha Leme Filho, M. S. Reiter, J. B. Campbell, and W. E. Thomason, "Comparing satellites and vegetation indices for cover crop biomass estimation," *Computers and Electronics in Agriculture*, vol. 196, p. 106900, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169922002174

[44] N. Wu, S. Weng, J. Chen, Q. Xiao, C. Zhang, and Y. He, "Deep convolution neural network with weighted loss to detect rice seeds vigor based on hyperspectral imaging under the sample-imbalanced condition," *Computers and Electronics in Agriculture*, vol. 196, p. 106850, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169922001673

[45] Y. Nan, H. Zhang, Y. Zeng, J. Zheng, and Y. Ge, "Intelligent detection of multi-class pitaya fruits in target picking row based on wgb-yolo network," *Computers and Electronics in Agriculture*, vol. 208, p. 107780, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169923001680

[46] K. Kusnierek and A. Korsaeth, "Simultaneous identification of spring wheat nitrogen and water status using visible and near infrared spectra and powered partial least squares regression," *Computers and Electronics in Agriculture*, vol. 117, pp. 200–213, 2015. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169915002240

[47] Y. Liu, J. Wang, Y. Shi, Z. He, F. Liu, W. Kong, and Y. He, "Unmanned airboat technology and applications in environment and agriculture," *Computers and Electronics in Agriculture*, vol. 197, p. 106920, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S016816992200237X

[48] C. Taylor, J. Guy, and J. Bacardit, "Estimating individual-level pig growth trajectories from group-level weight time series using machine learning," *Computers and Electronics in Agriculture*, vol. 208, p. 107790, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169923001783

[49] R. Belmonte, C. Cruz, and V. Fernández, *INTERVENCIONES SOBRE ESCULTURAS DEL PATRIMONIO*. Facultad de Educación Universidad de Extremadura Fundación CB, 01 2020, pp. 1171 – 1187.

[50] P. Shorten and L. Hunter, "Acoustic sensors for automated detection of cow vocalization duration and type," *Computers and Electronics in Agriculture*, vol. 208, p. 107760, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169923001485

[51] A. J. Gijsman, P. K. Thornton, and G. Hoogenboom, "Using the wise database to parameterize soil inputs for crop simulation models," *Computers and Electronics in Agriculture*, vol. 56, no. 2, pp. 85–100, 2007. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169907000038

[52] L. Liu, Y. Du, X. Li, T. Sun, W. Zhang, G. Li, L. Yang, D. Chen, and E. Mao, "An automatic forage unloading method based on machine vision and material accumulation model," *Computers and Electronics in Agriculture*, vol. 208, p. 107770, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169923001588

[53] D. M. S. Arsa, T. Ilyas, S.-H. Park, O. Won, and H. Kim, "Eco-friendly weeding through precise detection of growing points via efficient multi-branch convolutional neural networks," *Computers and Electronics in Agriculture*, vol. 209, p. 107830, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169923002181

[54] K. Tu, W. Wu, Y. Cheng, H. Zhang, Y. Xu, X. Dong, M. Wang, and Q. Sun, "Aiseed: An automated image analysis software for high-throughput phenotyping and quality non-destructive testing of individual plant seeds," *Computers and Electronics in Agriculture*, vol. 207, p. 107740, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S016816992300128X

[55] A. Andreadis, G. Giambene, and R. Zambon, "Design and analysis of a lora-based system with scheduled transmissions from iot nodes to uav in rural areas," *Ad Hoc Networks*, vol. 175, p. 103868, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1570870525001167

[56] A. Botta, P. Cavallone, L. Baglieri, G. Colucci, L. Tagliavini, and G. Quaglia, "A review of robots, perception, and tasks in precision agriculture," *Applied Mechanics*, vol. 3, no. 3, pp. 830–854, 2022. [Online]. Available: https://www.mdpi.com/2673-3161/3/3/49

[57] M. Huang, X. Jiang, L. He, D. Choi, J. Pecchia, and Y. Li, "Development of a robotic harvesting mechanism for button mushrooms," *Transactions of the ASABE*, vol. 64, no. 2, pp. 565–575, 2021. [Online]. Available: https://www.asabe.org/

[58] Y. Bai, B. Zhang, N. Xu, J. Zhou, J. Shi, and Z. Diao, "Vision-based navigation and guidance for agricultural autonomous vehicles and robots: A review," *Computers and Electronics in Agriculture*, vol. 205, p. 107584, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169922008924

[59] C. Kim, X. Yuan, M. Kim *et al.*, "Monitoring and risk analysis of residual pesticides drifted by unmanned aerial spraying," *Scientific Reports*, vol. 13, p. 10834, 2023, published: 05 July 2023. [Online]. Available: https://doi.org/10.1038/s41598-023-36822-w

[60] J. Campos, J. Llop, M. Gallart, F. García-Ruiz, A. Gras, R. Salcedo, and E. Gil, "Development of canopy vigour maps using uav for site-specific management during vineyard spraying process," *TBD*, vol. TBD, no. TBD, p. TBD, 2023, corresponding author: Emilio Gil, emilio.gil@upc.edu.

[61] P. Syropoulou, M. Symeonidou, S. Tekes, R. Wawer, A. Kazantzidis, V. Crnojevic, and A. Bruggeman, "Developing an intelligent decision support system for environmentally optimized irrigation management using sensors, remote sensing and meteorological forecast," *Journal of Agricultural Informatics*, vol. 8, no. 2, pp. 3–75, 2017. [Online]. Available: https://doi.org/10.17700/jai.2017.8.2.375

[62] S. Jain, D. Ramesh, E. Damodar Reddy, S. Rathod, and G. Ondrasek, "A fast high throughput plant phenotyping system using yolo and chan-vese segmentation," *Soft Comput.*, vol. 28, no. 20, p. 12323–12336, Aug. 2024. [Online]. Available: https://doi.org/10.1007/s00500-024-09946-y

[63] S. Hernandez-Marin, A. M. Wallace, and G. J. Gibson, "Bayesian analysis of lidar signals with multiple returns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 12, pp. 2170–2180, 2007.

[64] Y. Zhu, J. Zhuang, S. Ye, N. Xu, J. Xiao, J. Gu, Y. Fang, C. Peng, and Y. Zhu, "Domain generalization in nematode classification," *Computers and Electronics in Agriculture*, vol. 207, p. 107710, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169923000984

[65] H. Jiang, C. Zhang, Y. Qiao, Z. Zhang, W. Zhang, and C. Song, "Cnn feature based graph convolutional network for weed and crop recognition in smart farming," *Computers and Electronics in Agriculture*, vol. 174, p. 105450, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169919321349