



International Journal of Research in Agronomy

E-ISSN: 2618-0618
P-ISSN: 2618-060X
© Agronomy
NAAS Rating (2026): 5.20
www.agronomyjournals.com
2026; SP-9(4): 01-09
Received: 21-01-2026
Accepted: 23-02-2026

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Smart vegetable farming: AI and precision technologies a comprehensive review

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DOI: <https://www.doi.org/10.33545/2618060X.2026.v9.i4Sa.5319>

Abstract

The world needs more vegetables than ever before in the face of climate change variability, decreasing arable land, and a growing world population estimated to reach 9.7 billion by 2050. Conventional vegetable farming practices are no longer sufficient to meet these demands. Smart vegetable farming techniques that incorporate Artificial Intelligence (AI), Machine Learning (ML), computer vision, IoT, UAVs, robotics, and precision sensors have shown promising potential to solve these problems. This review article provides a comprehensive overview of the current state-of-the-art of AI and precision techniques applied to vegetable farming practices along the entire value chain of vegetable production: field sensors, irrigation management, disease/pest detection, yield forecasting, greenhouse management, post-harvest quality control, and vegetable supply chains. The findings of the review article are: deep learning-based AI models have shown disease detection accuracy of over 97%, precision irrigation techniques have shown a potential for saving 20-40% of irrigation water, and robotic harvesting has shown human-level performance for structured vegetable crops. Critical challenges such as high deployment costs, rural connectivity gaps, data privacy issues, and generalization of models are also highlighted by the literature review. Finally, the paper also provides a discussion on future research directions related to edge AI, digital twins, blockchain technology, and federated learning. In total, the paper is based on 80 peer-reviewed literature studies and provides seven comparative tables and five conceptual figures.

Keywords: Smart farming, artificial intelligence, precision agriculture, IoT, uavs, machine learning, vegetable production, deep learning, greenhouse automation, agricultural robotics

Introduction

Vegetable crops represent one of the most nutritionally important and economically valuable aspects of the global agricultural sector, which contributes over USD 1.1 trillion to the global food economy every year. However, conventional vegetable production systems are facing increasing risks of a number of critical issues, such as unpredictable precipitation patterns due to climate change, continuous soil degradation, labor shortages in rural areas, increasing input costs and rising occurrences of new vegetable diseases and pests. These issues highlight the need for revolutionary vegetable production systems to address these issues effectively.

The last ten years have seen an unprecedented integration of digital technologies in the agricultural sector. The term 'smart farming' has gained currency as a new paradigm for the application of information and communication technologies (ICT) such as AI, ML, IoT, UAVs and cloud computing to develop 'data-driven, highly adaptive and autonomous farm management systems' (Wolfert *et al.*, 2017; Klerkx *et al.*, 2019) [24, 71]. In the context of the 'smart farming' paradigm, vegetable farming is seen to have its own opportunities and challenges in terms of the high variety of crops grown, the sensitivity of the quality of the final product to local micro-climatic conditions, the high labor content of the farming process and the perishability of the final product.

Moreover, artificial intelligence-based systems allow farmers to monitor crops at all times through networked sensors and satellite images, diagnose diseases through images of leaves at near-expert levels of accuracy, forecast yields before harvest time at economic precision levels

and also irrigate crops autonomously depending on soil moisture and real-time weather conditions. Additionally, agricultural robots with computer vision are starting to assist in selective harvesting and blockchain-based platforms are starting to link production data to end-consumer products (Sharma *et al.*, 2021; Saiz-Rubio & Rovira-Más, 2020)^[49, 53]. Despite the large number of individual studies on these topics, there are limited comprehensive and integrative literature reviews that are specific to vegetable farming systems. Existing literature reviews focus on precision agriculture as a whole (Gebbers & Adamchuk, 2010; Liakos *et al.*, 2018)^[18, 29], or on specific crops such as cereals (Chlingaryan *et al.*, 2018; Bannerjee *et al.*, 2018)^[3, 8]. In this paper, a critical and structured literature review of AI and precision technologies for all phases of vegetable production is conducted. Seven data tables and five conceptual framework figures are included to assist with comparative analysis.

1.1 Scope and Objectives

The objectives of the review are three-fold: First and foremost, it aims to identify the current landscape of AI and precision

technologies in vegetable farming; secondly, it seeks to critically evaluate the performance and potential of different technologies; and lastly, it aims to identify research gaps and opportunities for future research in the domain of AI and precision technologies for vegetable farming. The review of the literature was done for the period of 2009-2024 from the Web of Science, Scopus, Google Scholar and IEEE Xplore databases using search terms such as 'smart farming,' 'vegetable production,' 'precision agriculture,' 'machine learning for crops,' 'agricultural IoT,' 'UAV farming,' 'agricultural robotics,' etc.

2. Conceptual Framework of Smart Vegetable Farming

Smart vegetable farming can be described as having a tripartite architectural framework that includes: (i) a Data Layer wherein various parameters of interest are sensed through heterogeneous sensor networks and aerial platforms; (ii) an Analytics Layer wherein data is processed through various AI algorithms to derive useful intelligence; and (iii) a Decision and Actuation Layer wherein the derived intelligence is used to drive various management actions. Figure 1 shows a conceptual framework of the architecture of smart vegetable farming.

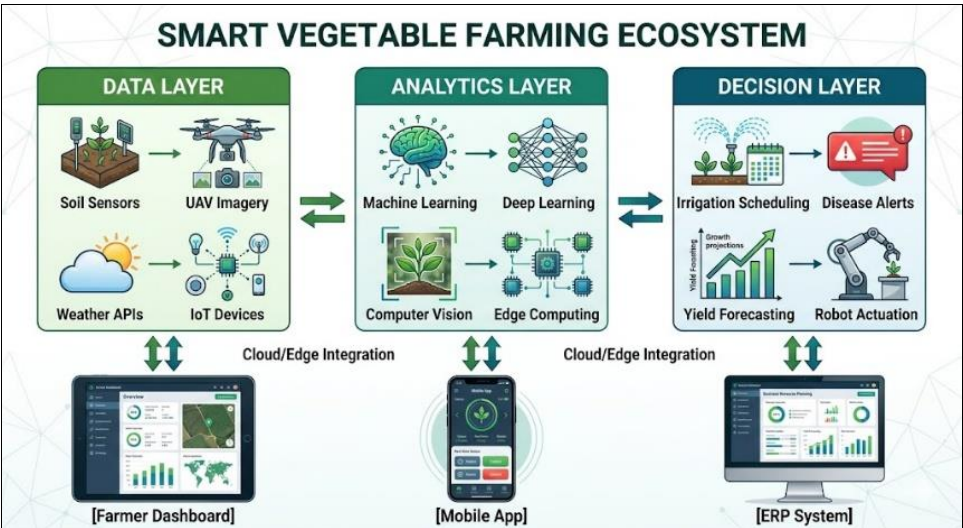


Fig 1: Conceptual framework of AI-enabled smart vegetable farming ecosystem.

The ecosystem brings together the advantages of edge computing and cloud computing, where the former focuses on the responsiveness of the system, while the latter focuses on the computational power required for the AI model (Navarro *et al.*, 2020)^[40]. The devices will be responsible for tasks such as the control of irrigation systems, while the cloud will be responsible for tasks such as the training of deep neural networks, among others. The farm management information systems (FMIS) will be the focal point for the integration, including dashboards, mobile apps and ERP systems (Fountas *et al.*, 2015)^[16].

3. Artificial Intelligence and Machine Learning in Vegetable Farming: 3.1 Overview of AI Technologies Applied

The range of AI techniques used in vegetable farming varies widely and includes traditional machine learning techniques such as support vector machines (SVM), random forests (RF), gradient boosting; deep learning techniques such as convolutional neural networks (CNN), recurrent neural networks (RNN), transformers and generative adversarial networks (GAN). Table 1 provides a summary of some of the AI techniques, their application domain, characteristics and references.

Table 1: Summary of major AI technologies applied in smart vegetable farming

Technology	Application Domain	Key Features	Representative Studies
Deep Learning (CNN)	Disease Detection	High accuracy (>95%), real-time image analysis	Mohanty <i>et al.</i> (2016); Ferentinos (2018) ^[13, 35]
Machine Learning (SVM/RF)	Yield Prediction	Multi-variable analysis, historical data training	van Klompenburg <i>et al.</i> (2020) ^[66]
Reinforcement Learning	Irrigation Scheduling	Adaptive decision-making, water savings 20-40%	Alibabaei <i>et al.</i> (2022) ^[1]
Computer Vision	Harvesting Robots	Object detection, 3D spatial mapping	Bac <i>et al.</i> (2014); Feng <i>et al.</i> (2020) ^[2, 14]
Natural Language Processing	Farmer Advisory Systems	Multilingual support, chatbot integration	Jha <i>et al.</i> (2019) ^[21]
Federated Learning	Privacy-Preserving Analytics	Decentralized model training, data privacy	Diao <i>et al.</i> (2021) ^[9]

3.2 Deep Learning for Image-Based Applications

The most impactful AI application in vegetable farming is undoubtedly image-based deep learning for plant disease detection, pest detection, fruit ripeness estimation and weed detection. Convolutional neural networks, pre-trained on large image datasets like ImageNet and fine-tuned on agricultural image datasets, have emerged as the most popular choice for image classification tasks in vegetable farming (Kamilaris & Prenafeta-Boldú, 2018; Kamilaris *et al.*, 2018) [22]. The PlantVillage image dataset, consisting of over 54,000 images of leaves from 38 classes of plant disease, has been instrumental in kick-starting this field by allowing researchers Mohanty *et al.* (2016) [35] to achieve classification accuracy of over 99% using

convolutional neural networks.

Nevertheless, classification accuracy on field images, accounting for variability in lighting, occlusion, soil background and early disease symptoms, has been observed to be consistently lower by 10-20% compared to accuracy on laboratory images (Liu & Wang, 2021) [28]. This has led researchers to focus on transfer learning, data augmentation, semi-supervised learning and few-shot learning methods for improving accuracy on field images (Li & Chao, 2022) [27]. Figure 2 shows the conventional architecture used for disease detection using deep learning algorithms.

Figure 2: Architecture of conventional deep learning algorithms used for disease detection.

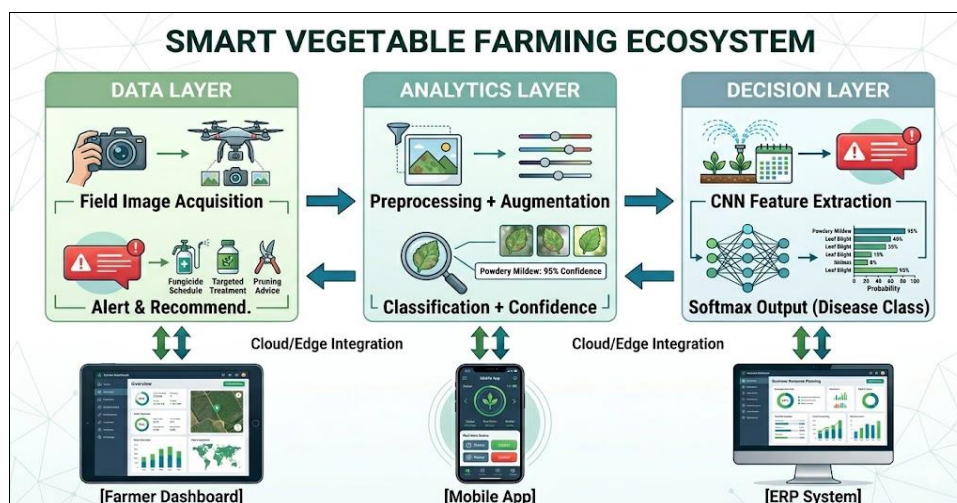


Fig 2: AI-driven crop disease detection workflow using convolutional neural networks (CNN).

3.3 Yield Prediction Models

Yield prediction is a critical aspect of strategy for farmers, traders and policymakers in food security policy-making circles. Machine learning models are now able to incorporate multi-modal inputs such as satellite-derived vegetation information, meteorological information, soil physicochemical properties, phenological stage information and historical yield information to make predictions weeks to months ahead of harvest season. According to a systematic review of 50 studies by Van Klompenburg *et al.* (2020) & li *et al.*, 2022 [66], ensemble models such as RF and gradient boost were the most dominant models for yield prediction compared to linear regression models, with mean absolute percentage errors of 5-15%.

LSTM networks have also shown promising results for yield prediction of greenhouse vegetables, for which environmental conditions are recorded at a sub-hourly resolution (Muruganantham *et al.*, 2022) [39]. Another promising research

frontier is the use of hybrid models that combine crop growth models such as DSSAT and AquaCrop with ML models, which have shown potential for better interpretability and lower data demands compared to traditional ML models (Pantazi *et al.*, 2016; Li *et al.*, 2020) [42, 26].

4. Precision Sensing Technologies

4.1 Soil and Environmental Sensors

The basis of any precise vegetable farming application is sound and reliable data acquisition from the physical environment. During the last decade or so, microelectronics and material sciences have enabled a significant decrease in the price of sensors for agriculture while increasing their accuracy considerably. Table 2 gives a comparative overview of important sensor modalities, parameters measured, performance characteristics and price ranges.

Table 2: Key sensor technologies for precision vegetable farming: parameters, accuracy and cost

Sensor Type	Parameter Measured	Accuracy Range	Cost (USD)	References
Soil Moisture	Volumetric Water Content	$\pm 2-3\%$	\$10-\$150	Hedley <i>et al.</i> (2013) [19]
EC Sensor	Electrical Conductivity	± 0.1 dS/m	\$50-\$500	Rhoades <i>et al.</i> (1999) [48]
Multispectral Camera	NDVI, Chlorophyll Index	± 5 nm band	\$500-\$5000	Xue & Su (2017) [72]
LiDAR	3D Crop Architecture	± 2 cm	\$1000-\$20000	Dworak <i>et al.</i> (2013) [10]
Thermographic Camera	Canopy Temperature	$\pm 0.5^\circ\text{C}$	\$300-\$3000	Bellvert <i>et al.</i> (2014) [4]
CO ₂ Sensor	Atmospheric CO ₂	± 30 ppm	\$100-\$800	Elsayed <i>et al.</i> (2011) [11]
Weather Station	Temp., Humidity, Rain, Wind	$\pm 0.1^\circ\text{C} / \pm 2\% \text{ RH}$	\$200-\$2000	Mogili & Deepak (2018) [34]

Soil moisture sensors utilizing time domain reflectometry (TDR), frequency domain reflectometry (FDR) and capacitance-based methods constitute the cornerstone of precision irrigation

management practices. Such sensors, when used in a distributed manner across various zones of the field, facilitate within-field variability mapping for variable rate irrigation prescriptions.

Simultaneously, the soil's electrical conductivity also serves as a proxy for soil salinity and texture, allowing for the identification of problem areas in greenhouse horticulture crops grown in saline soils (Rhoades *et al.*, 1999)^[48].

Multispectral and hyperspectral cameras mounted on towers or aerial platforms capture reflected radiation in tens to hundreds of discrete spectral bands. Vegetation indices such as NDVI, NDRE, SAVI, EVI and LAI estimation serve as non-destructive means for estimating chlorophyll content, biomass accumulation, nitrogen status and water stress (Xue & Su, 2017)^[72]. Thermal infrared cameras measure the surface temperature of the plant canopy, which is highly correlated to stomatal conductance and early water stress events (Bellvert *et al.*, 2014)^[4]. LiDAR scanners capture detailed 3D crop structures,

allowing for accurate estimation of crop canopy volume and robotic guidance within complex vegetable crops (Dworak *et al.*, 2013)^[10].

5. UAV-Based Remote Sensing in Vegetable Production

5.1 Platform Types and Capabilities

Unmanned aerial vehicles have rapidly progressed from research tools to operational farm management tools. Their potential for obtaining high-resolution images at user-specified times, unaffected by satellite revisit cycles or cloud conditions, makes them particularly attractive for the phenology of vegetable crops that are often time-sensitive. Table 3 provides a comparison of the main types of UAVs used for vegetable farming operations.

Table 3: UAV platform types and their capabilities for vegetable farming applications

UAV Type	Application	Coverage (ha/hr)	Accuracy	References
Fixed-Wing UAV	Large-area field mapping	50-200	5-10 cm GSD	Candiago <i>et al.</i> (2015) ^[6]
Multi-rotor UAV	Precision spraying	5-20	±0.5 m positioning	Huang <i>et al.</i> (2009) ^[20]
Hybrid VTOL	Disease scouting	20-80	3-7 cm GSD	Zhang & Kovacs (2012) ^[75]
Tethered UAV	Continuous monitoring	Stationary/limited	<2 cm GSD	Mesas-Carrascosa <i>et al.</i> (2015) ^[33]

5.2 Multi-temporal NDVI Monitoring

The most popular use of UAVs in vegetable farming is multi-temporal vegetation index monitoring for growth assessment, nitrogen management and pre-harvest yield estimation. Figure 3 shows a typical workflow for a vegetable farmer planning a zone-based variable rate application. By integrating NDVI maps

obtained from a UAV at critical growth stages of the crop with EC maps of the soil, farmers can design nutrient management zones for more effective nutrient use and prevent overuse of fertilizers, which could harm the environment (Yang *et al.*, 2017; Maes & Steppe, 2019)^[32, 73].

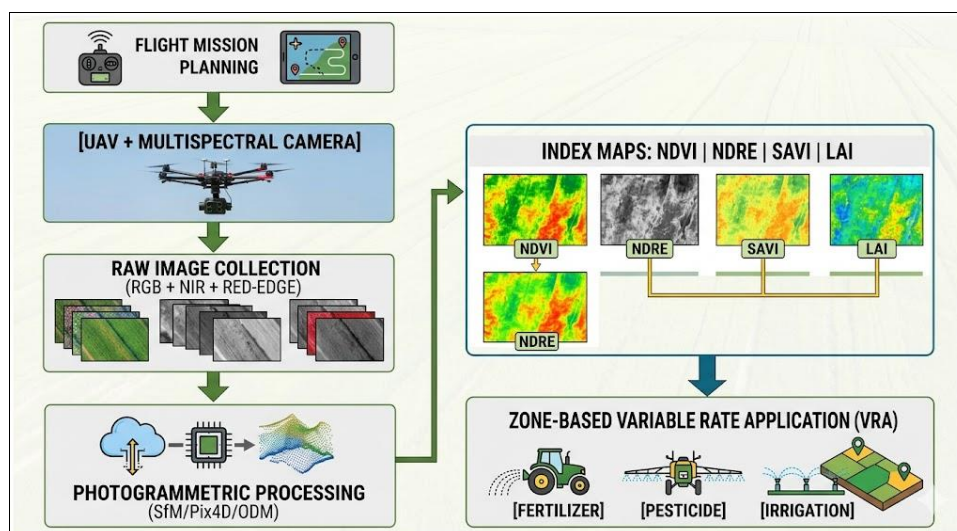


Fig 3: UAV-based multi-temporal NDVI monitoring for vegetable growth assessment.

Precision spraying UAVs are a growing market for these devices. These are provided with multi-nozzle spray equipment and GPS-based coverage logging, allowing for a 30-50% reduction in pesticide use compared to conventional ground-based equipment, according to Huang *et al.* (2013) and Mogili & Deepak (2018)^[20, 34], resulting from reduced drift and penetration loss. Zhang & Kovacs' paper (2012)^[75] provides a definitive overview of the use of UAVs for precision agriculture across a range of crops, highlighting that spectral analysis, crop scouting and spray application are the three most mature use cases for these devices.

6. Internet of Things (IoT) in Smart Vegetable Farming

6.1 IoT Architecture and Communication Protocols

The Internet of Things serves as the "connective tissue" to bring together disparate sensors, actuators, UAVs and computing platforms into a cohesive and responsive nervous system for the farm. The architectures for agricultural IoT systems usually consist of three layers: the field layer of embedded sensor and actuator nodes, the edge or fog layer of gateways and computing platforms and the cloud layer of AI systems, databases and applications (Navarro *et al.*, 2020; Vasisht *et al.*, 2017)^[40, 67].

Table 4: IoT communication protocols and their suitability for vegetable farming applications

Protocol	Range	Power Consumption	Data Rate	Best Use Case in Farming	Rwferences
LoRaWAN	2-15 km	Ultra-low	0.3-50 kbps	Remote soil sensor networks	Farooq <i>et al.</i> (2020); Tzounis <i>et al.</i> (2017); Morais <i>et al.</i> (2008) ^[12, 37, 64] .
Zigbee	10-100 m	Low	250 kbps	Greenhouse mesh networks	
NB-IoT	~10 km	Very low	~200 kbps	Nationwide agricultural monitoring	
Wi-Fi (802.11)	50-200 m	Moderate	Up to 9.6 Gbps	Controlled-environment agriculture	
5G Cellular	<1 km (dense)	Moderate-High	>1 Gbps	Real-time video analytics, robotics	
Satellite IoT	Global	High	1-100 kbps	Remote/off-grid farm telemetry	

The selection of the protocol is a significant aspect of the design process that must take into account the coverage range, power consumption, data rate and cost. LoRaWAN (Long Range Wide Area Network) has become the de facto standard for open-field applications, providing a range of kilometers while achieving battery life of years from a coin cell battery essential for a soil sensor network deployed at a high density where manual battery changes are not feasible (Farooq *et al.*, 2020)^[12]. In a greenhouse scenario, where a shorter range is not a concern and a mesh network can recover from node failures, Zigbee is a viable contender. Figure 4 shows the IoT-Cloud-Edge architecture for a smart farm scenario.

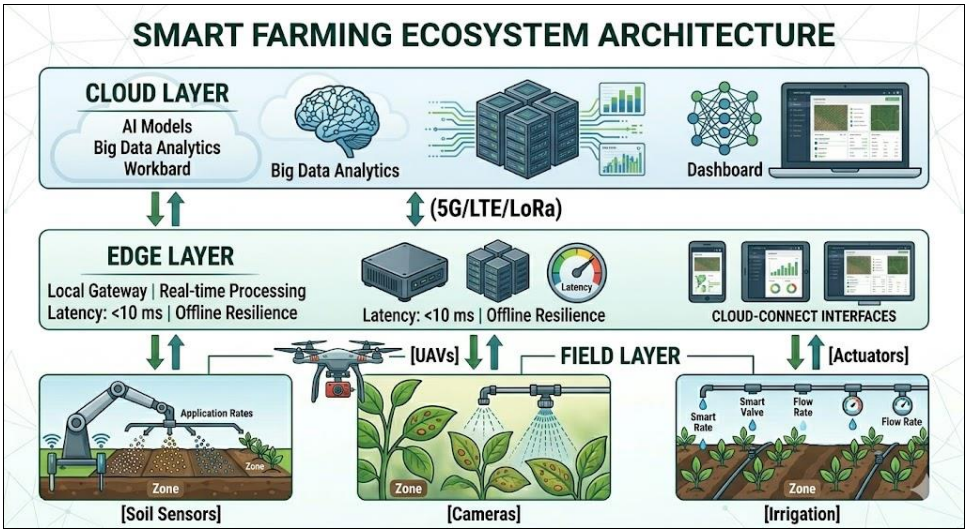


Fig 4: IoT-Cloud-Edge architecture for real-time smart farm monitoring and control.

7. AI-Driven Precision Irrigation Management

Water scarcity is one of the most critical limitations affecting vegetable production worldwide and irrigation systems account for approximately 70% of global freshwater withdrawals. Therefore, precision irrigation, which refers to providing the

"right amount of water, at the right location, at the right time," is one of the most promising areas of application for AI in agriculture and the complete pipeline for precision irrigation using AI is illustrated in Figure 5.

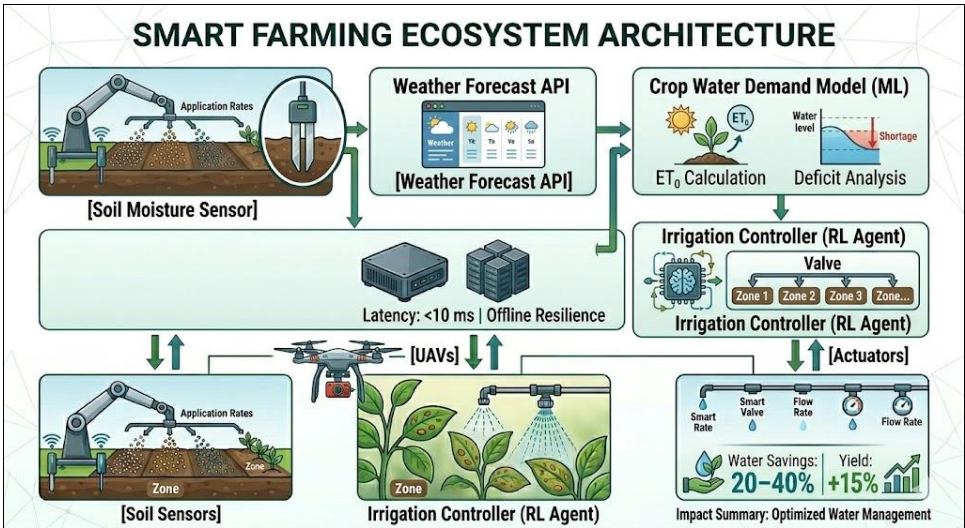


Fig 5: Precision irrigation decision system integrating soil moisture, weather forecasts and crop water demand models.

Current state-of-the-art in AI-based irrigation systems combines: (i) real-time soil moisture measurements via distributed sensor networks; (ii) weather forecast APIs for precipitation probability and ET₀ predictions; (iii) crop water demand modeling specific to crop type and growth stage; and (iv) reinforcement learning algorithms for continuous adaptation of irrigation schedules

based on outcomes. Alibabaei *et al.* (2022) & Mozgeris *et al.* (2018) ^[1, 38] showed that RL-based irrigation controllers always achieve 20-40% water savings without any yield penalty and, in many cases, achieve higher yields than conventional irrigation schedules due to reduced waterlogging.

Deficit irrigation is a water-saving strategy in which crops are subjected to a certain degree of water stress during non-critical growth stages. Such practices can be optimized through AI-based modeling to improve water productivity without any unacceptable penalties in terms of crop yields and quality. For instance, only AI-based modeling is capable of determining the optimal time for imposing water stress and allowing for subsequent recovery to achieve maximum water productivity ratios for specific crops grown in specific environments (Montanaro *et al.*, 2021) ^[36]. In greenhouse-grown tomatoes and cucumbers under drip irrigation systems, such optimized deficit

irrigation strategies have been shown to improve water productivity by 15-30% over crops receiving full irrigation.

8. AI-Based Plant Disease and Pest Detection

8.1 Deep Learning Model Performance Benchmarks

It has been estimated that plant diseases and pest infestation are accountable for an estimated loss of 20-40% of global crops every year and vegetable crops are no exception, being highly prone to disease because of their rapid growth rates, vulnerability to fungal and bacterial infections and their micro-environmental canopy structure. The possibility of conducting almost continuous disease detection at the plot scale, not feasible by human scouts, is promised by AI-powered disease detection systems. Table 5 shows a benchmark of key deep learning architectures used for vegetable disease detection.

Table 5: Performance benchmarks of deep learning models for vegetable disease detection

Model	Crop/Disease	Accuracy (%)	Dataset Size	References
VGG-16	Tomato leaf blight	96.3	18,000 images	Ferentinos (2018) ^[13]
ResNet-50	Multiple vegetables	97.8	PlantVillage ~54k	Too <i>et al.</i> (2019) ^[61]
MobileNetV2	Cucumber powdery mildew	94.1	6,400 images	Wang <i>et al.</i> (2019) ^[70]
Inception-V3	Pepper bacterial spot	95.7	12,500 images	Brahimi <i>et al.</i> (2017) ^[5]
YOLOv5	Tomato fruit detection	92.5 mAP	8,000 images	Li <i>et al.</i> (2022)
EfficientNet-B4	Lettuce diseases (4 classes)	98.2	21,000 images	Chen <i>et al.</i> (2021) ^[7]

The development from VGG-16 to lightweight architectures such as MobileNetV2 and EfficientNet is a major step forward in practical application, as disease-detecting models optimized for edge computing on low-power devices such as smartphones and Raspberry Pi allow for disease detection without the need for cloud connectivity, greatly increasing accessibility for smallholder farmers in low-bandwidth areas (Chen *et al.*, 2021; Fuentes *et al.*, 2017) ^[7, 16]. Object detection architectures, such as YOLOv5 and subsequent developments, have also been used to extend the ability to locate multiple lesions or pests within a single image to quantify disease severity as well as classify disease types (Li *et al.*, 2022) ^[27].

8.2 UAV-Based Disease Surveillance

The plot- to landscape-scale monitoring of disease development is not possible through single-plant-level ground detection. Zhang *et al.* (2019) & Liakos *et al.*, 2022 ^[29, 78]; have shown the potential of yellow rust detection through hyperspectral UAV images to attain 88.4% classification accuracy at a 50 m flight altitude, even before the development of visual symptoms. The 7- to 14-day advantages of early warning through UAV-based

disease detection compared to visual scouting allow for more effective preventive fungicide applications, which reduce the number of required applications (Sparks & Forbes, 2017; Tsouros *et al.*, 2015; Yeh *et al.*, 2020) ^[57, 63, 74]. Analysis of thermal images obtained through UAV-based disease detection provides another dimension for the detection of heat signatures of infected plants due to stomatal closure as a result of fungal infections.

9. Greenhouse Automation and Controlled Environment Agriculture

Protected horticulture, which includes glass houses, plastic tunnels and vertical farms, is the technologically most advanced and economically most developed form of smart vegetable production. CEA provides the prerequisites for a holistic approach to automation: a spatial layout that is uniform by nature, a physical infrastructure for installing sensors and actuators, a stable communication infrastructure and economic benefits that make investments in technology worthwhile. Table 6 provides an overview of the major components of smart greenhouse automation.

Table 6: Key automation subsystems in smart greenhouse vegetable production

System Component	Control Parameter	Technology Used	Outcome / Benefit	References
Climate Control	Temp., humidity, CO ₂	PID + ML controller	15-25% energy saving	Sedghi <i>et al.</i> (2021); Tzounis <i>et al.</i> (2017); Navarro <i>et al.</i> (2020); Lottes <i>et al.</i> (20216); Lu <i>et al.</i> (2019); Paraforos <i>et al.</i> (2017) and Pivoto <i>et al.</i> (2018) ^[30, 40, 41, 46, 51, 64] .
Lighting System	Photoperiod, light spectrum	LED + AI scheduling	30% energy reduction	
Irrigation/Fertigation	Water and nutrient dosing	EC/pH sensors + IoT	40% water use efficiency	
Pest Monitoring	Insect detection, trapping	Camera + CNN	Pesticide use reduced 60%	
Harvesting Robot	Fruit maturity and picking	3D vision + robotic arm	Comparable to human labor	
Data Management	All sensor data streams	Cloud/Edge computing	Real-time decision support	

The multi-layer AI-based climate control in contemporary greenhouses, which combines the predictive transpiration of crops and weather forecasts to pre-condition the greenhouse environment in response to expected temperature extremes, has

been shown to attain 15-25% savings in comparison to the reactive control of the PID method alone (Sedghi *et al.*, 2021) ^[51]. LED-based lighting systems, which have been designed to be controlled by dynamic photosynthesis-based predictive models

and price forecasts, have also been shown to attain 30% savings in the context of lettuce and basil cultivation while maintaining or improving crop quality. Robotic systems for the harvesting of tomatoes, cucumbers, peppers and strawberries have been designed to integrate 3D stereo vision, force-based end-effectors and AI-based classifiers for fruit maturity, attaining 8-12 seconds per fruit in comparison to the 4-6 seconds of human experts (Bac *et al.*, 2014; Zhao *et al.*, 2016; Vougioukas, 2019)^[2, 68, 79].

10. Post-Harvest Quality Assessment and Supply Chain Traceability

The use of AI also extends beyond the farm gate, including post-harvest quality evaluation, cold chain monitoring and supply chain traceability. Computer vision systems, for instance, can be implemented on grading lines to classify vegetables based on their size, color and shape, including the presence or absence of defects, at the rate of 2-6 items per second, which is much higher than the rate achievable by the human eye, with accuracy rates of 90-98% for major vegetables (Tian *et al.*, 2020; Patricio & Rieder, 2018)^[43, 60].

Hyperspectral imaging systems integrated into grading lines can

also look beyond surface quality attributes to internal quality attributes such as sugar content, firmness, dry matter content, etc., without destructive testing, making it possible to sort into premium tiers at commercial speeds (Sun *et al.*, 2019)^[59]. Blockchain technology, with the use of QR codes or RFID tags at harvest, can provide a permanent record of origin linking production data at the field level (inputs used, GPS coordinates, weather data, disease spray records) to consumer-facing traceability certificates an increasingly important requirement for premium export markets and food safety regulations (Ferrag *et al.*, 2020 & Plenet *et al.*, 2000)^[15].

11. Challenges and Barriers to Adoption

Despite the proven technical capacity of smart vegetable farming technologies, the large-scale adoption, especially in smallholder-dominated vegetable production systems, which dominate most Asian, African and Latin American countries, faces significant challenges due to a multitude of technical, economic, institutional and social hurdles. Table 7 provides a detailed mapping of the challenges and the suggested solutions, along with the literature.

Table 7: Key challenges to AI and precision technology adoption in vegetable farming and proposed solutions

Challenge	Description	Proposed Solutions	References
High Initial Cost	Capital-intensive hardware and software	Subsidy programs, shared-service models	Wolfert <i>et al.</i> (2017) & Singh <i>et al.</i> (2016) ^[55, 71]
Connectivity Gaps	Poor rural internet infrastructure	LoRa, satellite IoT, offline-first apps	Farooq <i>et al.</i> (2020) ^[12]
Data Privacy	Farmer data misuse by third parties	Federated learning, data cooperatives	Sharma <i>et al.</i> (2022) ^[54]
Skill Gap	Low digital literacy among smallholders	Training programs, simplified UI, voice interfaces	Klerkx <i>et al.</i> (2019) & Torres-Sánchez <i>et al.</i> 2015 ^[24, 62]
Model Generalizability	AI models trained in specific geographies	Transfer learning, domain adaptation	Kamilaris & Prenafeta-Boldú (2018) ^[22]
Cybersecurity	Vulnerable IoT nodes, data breaches	Blockchain, end-to-end encryption	Ferrag <i>et al.</i> (2020) & Salami <i>et al.</i> (2014) ^[15, 50]

The high initial cost of precision agriculture equipment such as sensor systems, UAVs, robots and greenhouse automation systems still poses a significant barrier to the adoption of precision agriculture by smallholder farmers. The concept of shared services, such as UAV spraying services and equipment cooperatives, as well as subsidy schemes by governments, have been shown to have the potential to provide precision agriculture services to smallholder farmers (Wolfert *et al.*, 2017; Klerkx *et al.*, 2019)^[24, 71]. The issue of digital illiteracy is equally fundamental. Even if the cost of precision agriculture equipment is low, the level of expertise required to interpret the data and manage the systems may be beyond the capacity of smallholder farmers. The concept of voice-enabled AI systems for farmers, which have been tested in India, Kenya and Indonesia, offers a lot of promise in reducing the illiteracy barrier to precision agriculture adoption (Jha *et al.*, 2019; Su *et al.*, 2019 & Sishodia *et al.*, 2020)^[21, 56].

12. Future Research Directions and Emerging Technologies

12.1 Edge AI and TinyML

The use of AI inference directly on low-power microcontrollers, known as TinyML, is seen as an enabling technology for the context of vegetable farming. The use of 8-bit or lower precision, architecturally optimized, low-parameter count models for disease detection or soil moisture inference can run on devices using only milliwatts of power, thus creating the potential for always-connected, battery-powered field nodes (Unal, 2020)^[65]. The use of edge AI along with energy

harvesting technologies like solar or piezoelectric offers the potential for always-connected, self-sustaining smart sensor deployments.

12.2 Digital Twins for Vegetable Production

The technology of digital twins i.e., real-time virtual representations of physical systems of interest in agriculture, such as farming systems, which are always up-to-date and synchronized with real-time data marks the boundary of the fusion of simulation modeling, IoT sensing technologies and artificial intelligence. The digital twin of a greenhouse vegetable crop, for instance, calibrated to real-time data and parameters of the vegetable's life cycle, can be used to test various scenarios of climate settings, irrigation schedules and harvest times without any risk to the real-life crop (Saiz-Rubio & Rovira-Más, 2020)^[49]. This is especially useful for managing complex multi-parameter interactions in CEA systems when the underlying system behavior is not intuitive.

12.3 Federated Learning and Data Cooperatives

The challenge of data privacy in agricultural AI can be directly addressed through the application of "federated learning" architectures for AI model training, wherein only updates to the gradients of the AI model are shared between the individual farm devices and a central "aggregation server," without any individual farm's data ever being shared (Diao *et al.*, 2021)^[9]. Agricultural data cooperatives the institutional structures through which groups of farmers collectively own and control their shared data provide the "governance innovation" necessary

to support the application of "federated learning" architectures for agricultural AI model development.

12.4 Explainable AI for Farmer Trust

One of the major barriers to adoption has been the level of trust farmers are willing to place in AI-based recommendations, particularly when there is a conflict with experiential knowledge. Explainable AI (XAI), a new branch of AI research, has begun to focus on providing explanations for AI model predictions, such as saliency maps showing where on a leaf the AI made a disease classification decision, or feature importance plots showing which weather variables contributed to a yield forecast. Studies showing the impact of XAI-based tools on increased trust and compliance rates for farmers who use AI-based tools will be essential to promoting adoption (Sharma *et al.*, 2021)^[53].

13. Conclusions

This review article has clearly established the significant impact AI and precision technologies are having on the entire range of vegetable cultivation, from seed to shelf. In fact, deep learning models have been found to be comparable or even superior to human expertise in the identification of diseases, estimation of crop yields and grading of vegetables. Precision irrigation systems, aided by RL agents, have been able to save up to 20-40% of irrigation water. Autonomous greenhouses have been able to control complex multi-variable environments more reliably than human operators. UAVs, along with multispectral and hyperspectral sensors, are revolutionizing farm-scale remote sensing.

Yet the distance between technological possibility and adoption in the field especially in smallholder systems remains large. This distance will require coordinated innovation across several fronts: lowering the cost of hardware through economies of scale and innovative business models; enhancing connectivity in rural areas through low-power wide-area network technologies; developing data governance structures that are farmer-centric but also respect privacy and enable collective intelligence; designing digitally enabled advisory services that are sensitive to cultural diversity and linguistic differences; and developing technical extension capacity to assist farmers in dealing with the increasing complexity of the digital agriculture environment.

The confluence of edge AI, digital twins, blockchain traceability, federated learning and advanced robotics individually emerging in agriculture has the potential to usher in a future of intelligent, adaptable and sustainable systems of vegetable production. However, it will require not only continued technological innovation but also commensurate social, institutional and policy innovation to ensure that these emerging technologies benefit all farmers, rather than just the privileged few.

References

1. Alibabaei K, Gaspar PD, Lima TM, Soares V. A review of the challenges of using deep learning algorithms to support decision-making in agricultural activities. *Remote Sens.* 2022;14(3):638.
2. Bac CW, Van Henten EJ, Hemming J, Edan Y. Harvesting robots for high-value crops: State-of-the-art review and challenges ahead. *J Field Robot.* 2014;31(6):888-911.
3. Bannerjee G, Sarkar U, Das S, Ghosh I. Artificial intelligence in agriculture: A literature survey. *Int J Sci Res Comput Sci Appl Manag Stud.* 2018;7(3):1-6.
4. Bellvert J, Zarco-Tejada PJ, Girona J, Fereres E. Mapping crop water stress index in a 'Pinot-noir' vineyard. *Precis Agric.* 2014;15(4):361-376.
5. Brahimi M, Boukhalifa K, Moussaoui A. Deep learning for tomato diseases. *Appl Artif Intell.* 2017;31(4):299-315.
6. Candiago S, Remondino F, De Giglio M, Dubbini M, Gattelli M. Evaluating multispectral images for precision farming. *Remote Sens.* 2015;7(4):4026-4047.
7. Chen J, Chen J, Zhang D, Sun Y, Nanekharan YA. Deep transfer learning for plant disease identification. *Comput Electron Agric.* 2021;173:105393.
8. Chlingaryan A, Sukkariah S, Whelan B. Machine learning for crop yield prediction. *Comput Electron Agric.* 2018;151:61-69.
9. Diao E, Ding J, Tarokh V. SemiFed: Semi-supervised federated learning. *arXiv.* 2021;arXiv:2011.08348.
10. Dworak V, Selbeck J, Dammer KH, Hoffmann M, Zarezadeh AA, Bobda C. Smart NDVI camera system. *Sensors.* 2013;13(2):1523-1538.
11. Elsayed S, Rischbeck P, Schmidhalter U. Reflectance sensors for drought-stressed barley. *Field Crops Res.* 2015;177:148-160.
12. Farooq MS, Riaz S, Abid A, Umer T, Zikria YB. Role of IoT in agriculture. *Electronics.* 2020;9(2):319.
13. Ferentinos KP. Deep learning models for plant disease detection. *Comput Electron Agric.* 2018;145:311-318.
14. Feng Q, Yang J, Liu Y, Tian H, Liu C, Li Z, *et al.* UAV remote sensing for vegetable mapping. *Remote Sens.* 2020;12(10):1668.
15. Ferrag MA, Shu L, Yang X, Derhab A, Maglaras L. Security in IoT-based agriculture. *IEEE Access.* 2020;8:32031-32045.
16. Fountas S, Carli G, Sørensen CG, Tsiropoulos Z, Cavalaris C, Vatsanidou A, *et al.* Farm management information systems. *Comput Electron Agric.* 2015;115:40-50.
17. Fuentes A, Yoon S, Kim SC, Park DS. Deep-learning-based plant disease detection. *Sensors.* 2017;17(9):2022.
18. Gebbers R, Adamchuk VI. Precision agriculture and food security. *Science.* 2010;327(5967):828-831.
19. Hedley CB. Precision agriculture for nutrient management. *J Sci Food Agric.* 2015;95(1):12-19.
20. Huang Y, Thomson SJ, Hoffmann WC, Lan Y, Fritz BK. UAV technologies in agriculture. *Int J Agric Biol Eng.* 2013;6(3):1-10.
21. Jha K, Doshi A, Patel P, Shah M. Automation in agriculture using AI. *Artif Intell Agric.* 2019;2:1-12.
22. Kamilaris A, Prenafeta-Boldú FX. Deep learning in agriculture. *Comput Electron Agric.* 2018;147:70-90.
23. Kamilaris A, Kartakoullis A, Prenafeta-Boldú FX. Big data analysis in agriculture. *Comput Electron Agric.* 2017;143:23-37.
24. Klerkx L, Jakku E, Labarthe P. Digital agriculture and smart farming. *NJAS Wagening J Life Sci.* 2019;90-91:100315.
25. Kotschi J, Müller-Sämann K. Organic agriculture and climate change. Bonn: IFOAM; 2004.
26. Li D, Wang R, Xie C, Liu L, Zhang J, Li R, *et al.* Rice disease detection using CNN. *Sensors.* 2020;20(3):578.
27. Li Y, Chao X. Few-shot learning for plant disease recognition. *Plant Methods.* 2022;17:1-10.
28. Liu J, Wang X. Plant disease detection using deep learning. *Plant Methods.* 2021;17(1):1-18.
29. Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D. Machine learning in agriculture. *Sensors.* 2018;18(8):2674.
30. Lottes P, Hoferlin M, Sander S, Müter M, Schulze P, Stachniss LC. Classification system for agricultural robots.

- In: IEEE ICRA; 2016. p. 5157-5163.
31. Lu Y, Yi S, Zeng N, Liu Y, Zhang Y. Rice disease identification using CNN. *Neurocomputing*. 2017;267:378-384.
 32. Maes WH, Steppe K. UAV remote sensing in agriculture. *Trends Plant Sci*. 2019;24(2):152-164.
 33. Mesas-Carrascosa FJ, Notario García MD, Meroño de Larriva JE, Sánchez de la Orden M, García-Ferrer Porras A. UAV orthomosaics for crop management. *Remote Sens*. 2015;7(10):12793-12814.
 34. Mogili UR, Deepak BBVL. Drone systems in precision agriculture. *Procedia Comput Sci*. 2018;133:502-509.
 35. Mohanty SP, Hughes DP, Salathé M. Deep learning for plant disease detection. *Front Plant Sci*. 2016;7:1419.
 36. Montanaro G, Trevisani S, Sperandio G, Cellini A. Precision irrigation using ML. *Agriculture*. 2021;11(3):235.
 37. Morais R, Valente A, Serôdio C. ZigBee device for remote sensing. *Comput Electron Agric*. 2008;62(2):94-106.
 38. Mozgeris G, Juodkienė V, Jonikavičius D, Straižys V, Bručas D, Khalsa SDS. Hyperspectral imaging for plants. *Remote Sens*. 2018;10(3):422.
 39. Muruganantham P, Wibowo S, Grandhi S, Samrat NH, Islam N. Crop yield prediction review. *Remote Sens*. 2022;14(1):1.
 40. Navarro E, Costa N, Pereira A. IoT solutions for smart farming. *Sensors*. 2020;20(15):4231.
 41. Paraforos DS, Fountas S, Griepentrog HW. In-field assessment of tillage systems. *Soil Tillage Res*. 2017;171:86-96.
 42. Pantazi XE, Moshou D, Alexandridis T, Whetton RL, Mouazen AM. Wheat yield prediction using machine learning. *Comput Electron Agric*. 2016;121:57-65.
 43. Patricio DI, Rieder R. Computer vision in precision agriculture. *Comput Electron Agric*. 2018;153:69-81.
 44. Pedersen SM, Lind KM, editors. *Precision agriculture: technology and economic perspectives*. Cham: Springer; 2017.
 45. Peng J, Wang Y, Zhang J, He Y, Ye D. Soil organic carbon estimation using UAV. *Sci Total Environ*. 2020;746:141198.
 46. Pivoto D, Waquil PD, Talamini E, Finocchio CPS, Dalla Corte VF, Mores G. Smart farming technologies in Brazil. *Inf Process Agric*. 2018;5(1):21-32.
 47. Plénet D, Lemaire G. Nitrogen uptake and dry matter in maize. *Plant Soil*. 2000;216(1-2):65-82.
 48. Rhoades JD, Chanduvi F, Lesch S. *Soil salinity assessment*. Rome: FAO; 1999.
 49. Saiz-Rubio V, Rovira-Más F. Agriculture 5.0 perspective. *Agronomy*. 2020;10(2):207.
 50. Salami E, Barrado C, Pastor E. UAV experiments in vegetation sensing. *Remote Sens*. 2014;6(11):11051-11081.
 51. Sedghi M, Golzarian MR, Ashtiani SHM. Smart greenhouse monitoring via IoT. *Comput Electron Agric*. 2021;183:106028.
 52. Sharma R, Kamble SS, Gunasekaran A, Kumar V, Kumar A. Machine learning in agriculture supply chains. *Comput Oper Res*. 2020;119:104926.
 53. Sharma A, Jain A, Gupta P, Chowdary V. Machine learning in precision agriculture. *IEEE Access*. 2021;9:4843-4873.
 54. Sharma R, Kumar R, Bhatt A. Data privacy in precision agriculture. *Comput Electron Agric*. 2022;194:106731.
 55. Singh A, Ganapathysubramanian B, Singh AK, Sarkar S. Machine learning for plant phenotyping. *Trends Plant Sci*. 2016;21(2):110-124.
 56. Sishodia RP, Ray RL, Singh SK. Remote sensing in precision agriculture. *Remote Sens*. 2020;12(19):3136.
 57. Sparks AH, Forbes GA. Precision technologies in disease forecasting. *Phytopathology*. 2017;107(10):1199-1207.
 58. Su W, Minzan L. Remote sensing-based crop monitoring. *Int J Agric Biol Eng*. 2019;12(4):1-10.
 59. Sun S, Di L, Han W, Yu E, Zhang C, Lin L. Deep learning for plant identification. *Comput Intell Neurosci*. 2019;2019:1-10.
 60. Tian H, Wang T, Liu Y, Qiao X, Li Y. Computer vision in agricultural automation. *Inf Process Agric*. 2020;7(1):1-19.
 61. Too EC, Yujian L, Njuki S, Yingchun L. Deep learning models for plant disease identification. *Comput Electron Agric*. 2019;161:272-279.
 62. Torres-Sánchez J, López-Granados F, Peña JM. UAV-based vegetation detection. *Comput Electron Agric*. 2015;114:43-52.
 63. Tsouros DC, Bibi S, Sarigiannidis PG. UAV applications in precision agriculture. *Information*. 2019;10(11):349.
 64. Tzounis A, Katsoulas N, Bartzanas T, Kittas C. IoT in agriculture. *Biosyst Eng*. 2017;164:31-48.
 65. Unal Z. Deep learning in smart farming. *IEEE Access*. 2020;8:105587-105609.
 66. van Klompenburg T, Kassahun A, Catal C. Crop yield prediction using ML. *Comput Electron Agric*. 2020;177:105709.
 67. Vasisht D, Kapetanovic Z, Won J, Jin X, Chandra R, Sinha S, *et al*. FarmBeats: IoT platform for agriculture. In: *USENIX NSDI*; 2017. p. 515-529.
 68. Vougioukas SG. Agricultural robotics. *Annu Rev Control Robot Auton Syst*. 2019;2:365-392.
 69. Wang G, Sun Y, Wang J. Image-based plant disease severity estimation. *Comput Intell Neurosci*. 2017;2017:1-8.
 70. Wang Q, Qi F, Sun M, Qu J, Xue J. Tomato disease detection using CNN. *Comput Intell Neurosci*. 2019;2019:1-10.
 71. Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big data in smart farming. *Agric Syst*. 2017;153:69-80.
 72. Xue J, Su B. Vegetation indices in remote sensing. *J Sens*. 2017;2017:1353691.
 73. Yang G, Liu J, Zhao C, Li Z, Huang Y, Yu H, *et al*. UAV remote sensing for crop phenotyping. *Front Plant Sci*. 2017;8:1111.
 74. Yeh C, Perez A, Driscoll A, Azzari G, Tang Z, Lobell D, *et al*. Satellite imagery and deep learning in Africa. *Nat Commun*. 2020;11(1):1-11.
 75. Zhang C, Kovacs JM. UAV systems in precision agriculture. *Precis Agric*. 2012;13(6):693-712.
 76. Zhang M, Shi W, Chen S, Zhan Z, Yan H. Deep learning for remote sensing. *IEEE Geosci Remote Sens Mag*. 2021;9(2):132-151.
 77. Zhang Q, editor. *Precision agriculture technology for crop farming*. Boca Raton: CRC Press; 2016.
 78. Zhang X, Han L, Dong Y, Shi Y, Huang W, Han L, *et al*. Yellow rust disease detection using UAV. *Remote Sens*. 2019;11(13):1554.
 79. Zhao Y, Gong L, Huang Y, Liu C. Vision-based control for harvesting robots. *Comput Electron Agric*. 2016;127:311-323.
 80. Zheng YY, Kong JL, Jin XB, Wang XY, Su TL, Zuo M. CropDeep dataset for precision agriculture. *Sensors*. 2019;19(5):1058.