Plant Archives Vol. 26, No. 2, 2026 pp. 2213-2217 e-ISSN:2581-6063 (online), ISSN:0972-5210

Plant Archives

Journal homepage: http://www.plantarchives.org

DOI Url : https://doi.org/10.51470/PLANTARCHIVES.2026.v26.no.2.303

SMART HORTICULTURE: COMBINING IOT, ROBOTICS, AND ARTIFICIAL INTELLIGENCE THROUGHOUT THE ENTIRE SUPPLY CHAIN

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(Date of Receiving-16-07-2026; Date of Revision-21-09-2026; Date of Acceptance-01-10-2026)

ABSTRACT

The increasing pressure on horticultural crop systems from population growth, labour shortages, and climate variability has created an interest in digital enabled or “smart” production models. This review summarizes recent developments in the horticultural value chain, from genomic-assisted breeding to precision cultivation, robotic harvesting, and blockchain-enabled traceability. Artificial intelligence (AI) and machine learning now drive the prediction of the genomic-envirome in breeding programs, real-time control of the environment in protected cultivation, and computer-vision-guided detection of fruit for autonomous harvesters. The Internet of Things (IoT) sensor networks and low-power wide-area communication protocols enable continuous tracking of soil, canopy and microclimate variables. Distributed ledger technologies are being used more and more to secure post-harvest quality and provenance records. Technical progress has been significant, but adoption is still limited by fragmented data infrastructure, high costs of robotics that can be used in the field, and a persistent gap between engineering and horticultural expertise. The review concludes by highlighting research priorities, such as interoperable data standards, low-cost sensing, and generalisable robotic platforms, required for the transition of smart horticulture from pilot studies to routine industrial practice.

***Key words*:** Smart horticulture, Artificial intelligence, Internet of Things (IoT), Robotic harvesting, Precision cultivation and Genomic-environmic prediction.

Introduction

Horticultural crops fruits, vegetables, ornamentals, and beverage crops such as tea supply a disproportionate share of dietary micronutrients relative to staple grain crops, yet their production remains comparatively labor-intensive and difficult to mechanize. Rising global demand, a shrinking agricultural workforce, and increasingly erratic weather have exposed the limits of conventional, experience-driven management. In response, a new generation of digital technologies AI, IoT, robotics, and blockchain is being layered onto horticultural production in what several authors describe as an emerging “Agriculture 5.0” transition, extending earlier waves of mechanization and automation toward fully data-driven decision-making (Zhang *et al.*, 2024).

Table 1: Summary of digital technologies applied across the horticultural production chain.

Stage	Core Digital Technologies	Primary Function	Representative Sources
Breeding	Machine learning on multi-omics + environmental data (iGEP); RGB/ hyperspectral/depth phenotyping	Predicts genotype performance across environments; accelerates selection	Xu *et al.*, 2022; Manowarul Islam *et al.*, 2023
Cultivation	IoT sensor networks (LoRaWAN, ZigBee); edge/fog ML (LSTM, SVM); automated irrigation & fertigation	Continuous monitoring and predictive, model-driven environmental control	Zhang, He & Di Gioia, 2023; Saranya *et al.*, 2023; Ojo & Zahid, 2022
Harvesting	CNN/YOLO object detection; 3D point-cloud and amodal segmentation; low-DOF robotic manipulators	Locates ripe produce amid occlusion and executes damage-free picking	Jocher *et al.*, 2023; Yu *et al.*, 2022; Kim *et al.*, 2023; Hu *et al.*, 2022; Rong *et al.*, 2022
Post-Harvest	Blockchain ledgers; IoT cold-chain sensors; smart contracts; deep-learning anomaly detection	Secures provenance records and flags storage/handling deviations	Kamble *et al.*, 2020; Kumar *et al.*, 2023; Kumar, Murthy, Pillai & Prathap, 2022

Unlike row-crop agriculture, horticultural production is organized around discrete, high-value stages breeding, protected or open-field cultivation, harvest, and post-harvest handling each with distinct technological needs. This review examines how AI-, IoT-, and robotics-based tools are being applied at each stage, drawing on recent peer-reviewed literature, and identifies the structural barriers that continue to slow adoption across the sector. Table 1 summarizes the core technologies, their primary function, and representative sources for each stage discussed in this review.

Smart Breeding

From Genomic Selection to Genomic-Enviromic Prediction:

Molecular marker-assisted selection has revolutionised horticultural breeding in the past three decades, but conventional genomic prediction models generally do not consider the performance of genotypes across environments. Xu *et al.*, (2022) propose to extend genomic prediction into a comprehensive genomic-enviromic prediction (iGEP) paradigm, where machine learning algorithms are trained on multi-omics and environmental time-series data to predict the performance of a given genotype under a specific climate and management regime. This change shifts the paradigm of breeding from a search for a single "best" genotype to a directional process that is sensitive to the environment and is especially relevant for horticultural crops grown in highly variable microclimates ranging from open fields to controlled greenhouses.

High-throughput phenotyping is the foundation of AI-assisted breeding pipelines as it provides the labelled data needed for these models. Imaging platforms based on RGB, hyperspectral and depth sensing are increasingly exploited for non-destructive scoring of morphological and physiological traits at scale, directly feeding genomic-enviromic models and shortening the traditional breeding cycle. This data pipeline can be extended from the breeding nursery to commercial production by deployment of deep learning-based disease and stress prediction tools like web-deployed crop disease classifiers (Manowarul Islam *et al.*, 2023).

Smart Cultivation

Sensor Networks and Environmental Automation:

Protected cultivation (greenhouses, high tunnels, and soilless systems) is the most automatable part of horticulture because the environmental variables (temperature, humidity, CO_2, light, and root-zone moisture or nutrient status) can be sensed and actuated continuously. Low-power wide-area network protocols such as LoRaWAN and ZigBee have become the dominant communication backbone for these deployments, allowing dense arrays of soil-moisture, electrical-conductivity, and microclimate sensors to report to cloud platforms at minimal energy cost (Zhang, Heand Di Gioia, 2023). Fig. 2. illustrates a representative architecture linking field sensors, edge/fog inference, cloud analytics, and actuation.

Field and greenhouse trials of IoT-based precision irrigation have consistently reported water savings with

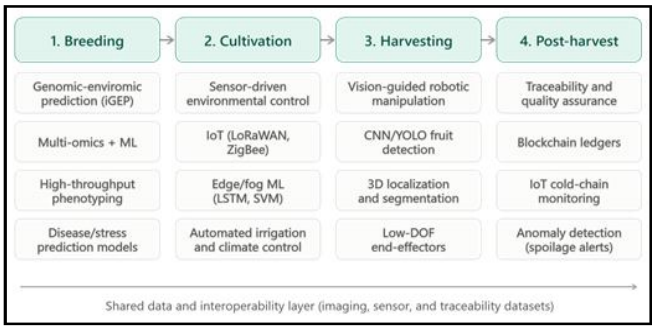


Fig. 1: Technology integration across the smart horticulture production chain, from breeding through post-harvest handling.

Table 2: Selected robotic harvesting systems, by crop, perception approach, and manipulation strategy.

Crop	Perception Approach	Manipulation Approach	Key Reported Challenge
Pomegranate	Improved F-PointNet with 3D point-cloud clustering	Localization feeds downstream picking-point estimation	Fruit clustering and orchard clutter (Yu *et al.*, 2022)
Cucumber	Amodal segmentation to infer occluded boundaries	Boundary estimate supports grasp planning under foliage	Recovering shape from partial occlusion (Kim *et al.*, 2023)
Table grape	Monocular depth estimation + CNN for cluster/peduncle detection	Peduncle localization guides cutting position	Precise peduncle localization for clean cuts (Coll-Ribes *et al.*, 2023)
Apple	Standard CNN-based fruit detection	Simplified 4-DOF manipulator to cut cost/complexity	Balancing picking speed with mechanical simplicity (Hu *et al.*, 2022)
Watermelon	Vision system for pose and ripeness estimation	Dedicated gripper sized for irregular, heavy fruit	Judging cutting angle from irregular fruit pose (Rong *et al.*, 2022)

yield or quality increases. In a controlled trial on soilless basil production, an IoT-based irrigation system triggered by soil matric potential and volumetric water content sensors delivered water automatically and site-specifically, maintaining crop quality (Zhang, Heand Di Gioia, 2023). Similar hydroponic fertigation systems integrating wireless microclimate monitoring and automated nutrient dosing have reported simultaneous increases in yield and water productivity compared with conventional drip-irrigated soil culture . Edge- and fog-computing architectures are used to run lightweight machine learning algorithms such as long short-term memory networks and support vector machines directly on local gateways, in addition to irrigation, to reduce latency for climate-control actuation in commercial greenhouses (Saranya, Deisy, Srideviand Anbananthen, 2023). Deep learning is also being applied to controlled-environment agriculture more broadly, including vertical farms, where models trained on canopy imagery support early detection of nutrient deficiency and disease before visible symptoms appear across a stand (Ojo & Zahid, 2022). These systems collectively represent a shift from threshold-based automation toward predictive, model-based environmental control. Most reported deployments are still at research-scale, rather than commercial.

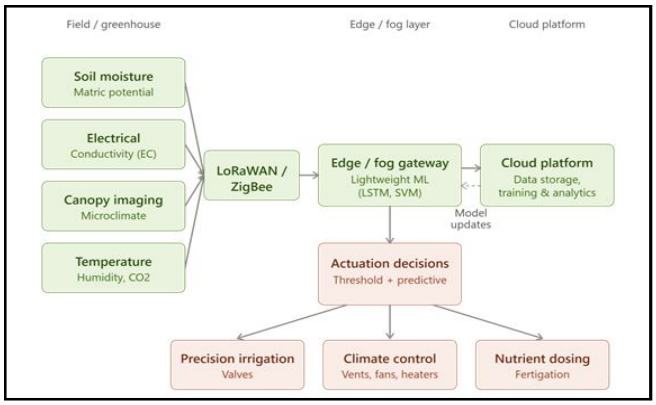


Fig. 2: Predictive Environmental Control in Protected Cultivation: Edge Computing and IoT Sensor Network Architecture.

Smart Harvesting:

Computer Vision and Robotics Manipulation:

Harvest remains the least mechanized stage of horticultural production, owing to the difficulty of reliably cluttered orchard and greenhouse scenes (Jocher, Chaurasiaand Qiu, 2023). Building on this backbone, researchers have developed crop-specific detection and localisation pipelines (Table 2).

Crop Perception Approach Manipulation Approach Main Reported Challenge Pomegranate Improved F-PointNet with 3D point-cloud clustering Localisation feeds downstream picking-point estimation Fruit clustering and orchard clutter (Yu *et al.*, 2022). Cucumber Amodal segmentation for occluded boundary inference Boundary estimate enables grasp planning under foliage Recovering shape from partial occlusion (Kim *et al.*, 2023) Table grape Monocular depth estimation + CNN for cluster/ peduncle detection Cutting position guided by peduncle localisation Accurate peduncle localisation for clean cuts (Coll-Ribes *et al.*, 2023). Apple Standard CNN-based fruit detection Simplified 4-DOF manipulator to reduce cost/complexity Achieving a balance between picking speed and mechanical simplicity (Hu *et al.*, 2022). Watermelon Vision system for pose and ripeness estimation Dedicated gripper sized for irregular and heavy fruit Determining cutting angle from irregular fruit pose (Rong *et al.*, 2022). Once the target is located, the success of harvesting depends on the end-effector design and the manipulator kinematics. Dedicated vision-and-gripper systems have been developed to target irregularly shaped crops such as watermelon, for which the picking point and cutting angle have to be judged from the fruit pose in the canopy (Rong *et al.*, 2022). Simplified low-degree-of-freedom manipulators have been proposed to reduce the cost and complexity of control of apple-harvesting arms while maintaining picking speed (Hu *et al.*, 2022). "A recent review of target-recognition methods for fruit-picking robots traces this progression from classical digital image processing toward end-to-

Table 3: Structural challenges in smart horticulture adoption and corresponding research priorities.

Structural Challenge	Manifestation	Recommended Research Priority
Limited data generalization	Models trained on small, cultivar- and site-specific datasets transfer poorly to new cultivars, regions, or camera hardware	Open, shared multi-cultivar phenotyping and imaging datasets
Engineering–agronomy disconnect	Robotics/vision groups optimize benchmark accuracy while horticultural scientists prioritize agronomic outcomes	Cross-disciplinary research programs bridging both communities
High cost of field-ready systems	Robotic harvesters and dense sensor networks are economical mainly for high-value crops or large operations	Modular, lower-cost, reconfigurable robotic platforms
Fragmented data infrastructure	Sensor, breeding, and traceability data remain siloed across incompatible systems	Interoperable data standards for unified decision-support systems
Latency and connectivity limits	Real-time control is constrained in remote or bandwidth-limited growing regions	Deeper integration of edge computing with AI inference

end deep learning, noting that occlusion, illumination variability, and the diversity of horticultural cultivars remain the dominant sources of detection failure in field deployment (Hua *et al.,* 2023).

Post-Harvest Management and Blockchain Enabled Traceability

Post-harvest losses in horticultural supply chains are caused by biological deterioration (respiration, moisture loss, microbial decay) and by information failures (the inability to verify storage conditions or provenance as produce moves between growers, processors and retailers). The latter problem is suggested to be addressed by the blockchain technology. It establishes an immutable shared record of handling events across a supply chain. Kamble, Gunasekaran and Sharma (2020) model the reduction of information asymmetry between supply-chain actors enabled by blockchain traceability, while more recent architectures combine blockchain ledgers with IoT sensor streams and intelligent contracts to automatically log temperature and humidity excursions during cold-chain transport, with deep-learning-assisted anomaly detection flagging deviations for intervention (Kumar *et al.*, 2023). These implementations in some sectors demonstrate the pragmatic framing of these systems. The blockchain-based models, explicitly created to decrease horticultural post-harvest losses, blend batch-level provenance records with predictive spoilage alerts (Kumar, Murthy, Pillaiand Prathap, 2022). However, empirical implementations also expose integration challenges interoperability between enterprise-grade and public blockchain networks, the computational overhead of privacy-preserving verification methods, and the difficulty of maintaining a single source of truth across a fragmented, multi-actor supply chain that still limit blockchain traceability to pilot projects rather than sector-wide standards.

Challenges and Outlook.

Three structural challenges recur in the literature reviewed. First, the majority of AI models in horticulture are trained on very small, cultivar- and site-specific datasets, which leads to poor generalisation when transferred to new cultivars, growing regions or camera hardware. This is especially critical for harvesting robots, whose vision systems have to cope with wide variations in fruit colour, shape and occlusion pattern over seasons and varieties. Second, the engineering and horticultural research communities are loosely coupled: robotics and computer-vision groups optimise for benchmark accuracy, horticultural scientists optimise for agronomic outcomes, and few research programs connect both. Third, cost remains a barrier. Field-ready robotic harvesters and dense sensor networks are often economically viable only for high-value crops or large operations, leaving smallholder horticulture largely outside the current wave of automation.

Filling these gaps will likely require open, shared phenotyping and imaging datasets across multiple cultivars and growing regions; modular, lower-cost robotic platforms that can be reconfigured across crops rather than built as single-purpose machines; and interoperable data standards that enable sensor, breeding, and traceability data to be integrated into unified decision-support systems. The ongoing integration of edge computing with AI inference should also bring down the latency and connectivity demands that presently limit real-time control in remote or bandwidth-constrained growing areas. Table 3 links each structural challenge with a corresponding research priority.

Poor data generalisation Models trained on small, cultivar- and site-specific datasets don't transfer well to new cultivars, regions and camera hardware Open, shared multi-cultivar phenotyping and imaging datasets. Engineering–agronomy disconnect Robotics/vision groups focus on benchmark accuracy; horticultural scientists focus on agronomic outcomes. Cross-disciplinary research programs linking the two communities. High price of field ready systems Robotic harvesters and dense sensor networks are cost-effective mainly for high value crops

or large operations. Modular, lower cost, reconfigurable robotic platforms. Fragmented data infrastructure Incompatible systems to store traceability, breeding and sensor data Interoperable data standards for integrated decision support systems. Latency and connectivity limitations Real-time control is restricted in remote/ bandwidth-limited growing areas. More integration of edge computing with AI inference

Summary

AI, IoT and blockchain technologies are converging into an increasingly integrated smart horticulture paradigm that covers breeding, cultivation, harvesting and post-harvest handling. Genomic-enviromic prediction is transforming breeding strategies, IoT-enabled sensor networks are pushing protected cultivation toward predictive rather than reactive control, computer-vision guided robots are slowly bridging the gap in harvesting automation and blockchain-linked traceability systems are beginning to secure post-harvest quality information. However, realising the full productivity and sustainability gains of these technologies will depend less on further algorithmic refinement and more on tackling the practical problems of data standardisation, cost and cross-disciplinary collaboration that currently separate research prototypes from everyday horticultural practice.

References

Coll-Ribes, G., Torres-Rodríguez I.J., Grau A., Guerra E. and Sanfeliu A. (2023). Accurate detection and depth estimation of table grapes and peduncles for robot harvesting, combining monocular depth estimation and CNN methods. *Computers and Electronics in Agriculture*, **215**, 108362.

Hu, G., Chen C., Chen J., Sun L., Sugirbay A. and Chen Y. (2022). Simplified 4-DOF manipulator for rapid robotic apple harvesting. *Computers and Electronics in Agriculture*, **199**, 107177.

Hua, X., Li H., Zeng J., Han C., Chen T., Tang L. and Luo Y. (2023). A review of target recognition technology for fruit picking robots: From digital image processing to deep learning. *Applied Sciences*, **13(7)**, 4160.

Jocher, G., Chaurasia A. and Qiu J. (2023). Ultralytics YOLO (Version 8.0.0) [Computer software].

Kamble, S.S., Gunasekaran A. and Sharma R. (2020). Modeling the blockchain enabled traceability in agriculture supply chain. *International Journal of Information Management*, **52**, 101967.

Kim, S., Hong S.J., Ryu J., Kim E., Lee C.H. and Kim G. (2023). Application of amodal segmentation on cucumber segmentation and occlusion recovery. *Computers and Electronics in Agriculture*, **210**, 107847.

Kumar, K.P., Murthy H., Pillai V.J. and Prathap B.R. (2022). Blockchain-enabled model for minimizing post-harvest losses. *ECS Transactions*, **107(1)**, 17475–17482.

Kumar, R., Kumar P., Aljuhani A., Islam A.K.M.N., Jolfaei A. and Garg S. (2023). Deep learning and smart contract-assisted secure data sharing for IoT-based intelligent agriculture. *IEEE Intelligent Systems*, **38(4)**, 42–51.

Islam, M.M., Adil M.A.A., Talukder M.A., Ahamed M.K.U., Uddin M.A., Hasan M.K. and Debnath S.K. (2023). DeepCrop: Deep learning-based crop disease prediction with web application. *Journal of Agriculture and Food Research*, **14**, 100764.

Ojo, M.O. and Zahid A. (2022). Deep learning in controlled environment agriculture: A review of recent advancements, challenges and prospects. *Sensors*, **22(20)**, 7965.

Rong, J., Wang P., Yang Q. and Huang F. (2022). Development and evaluation of a watermelon-harvesting robot prototype: Vision system and end-effector. *Agronomy*, **12(11)**, 2836.

Saranya, T., Deisy C., Sridevi S. and Anbananthen K.S.M. (2023). A comparative study of deep learning and Internet of Things for precision agriculture. *Engineering Applications of Artificial Intelligence*, **122**, 106034.

Xu, Y., Zhang X., Li H., Zheng H., Zhang J., Olsen M.S., Varshney R.K., Prasanna B.M. and Qian Q. (2022). Smart breeding driven by big data, artificial intelligence, and integrated genomic-enviromic prediction. *Molecular Plant*, **15(11)**, 1664–1695.

Yu, T., Hu C., Xie Y., Liu J. and Li P. (2022). Mature pomegranate fruit detection and location combining improved F-PointNet with 3D point cloud clustering in orchard. *Computers and Electronics in Agriculture*, **200**, 107233.

Zhang, H., He L. and Di Gioia F. (2023). Implementing Internet of Things (IoT) sensor-based precision irrigation with LoRaWAN technology for enhancing yield, quality, and resource use efficiency of soilless basil. *Acta Horticulturae*, **1377**, 647–654.

Zhang, S., Zhang C., Yang C. and Liu B. (2024). Editorial: Artificial intelligence and Internet of Things for smart agriculture. *Frontiers in Plant Science*, **15**, 1494279.