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ARTIFICIAL INTELLIGENCE AS A TRANSFORMATIVE TOOL IN HORTICULTURAL SCIENCE APPLICATIONS, ADVANCES, AND FUTURE PROSPECTS

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ABSTRACT

The rapid advancement of artificial intelligence (AI) has opened transformative possibilities for horticultural science, offering intelligent solutions to persistent challenges across crop production systems. AI encompasses computational frameworks engineered to simulate human cognitive functions including perception, adaptive learning, and data-driven decision-making through algorithmically driven models. In horticulture, these capabilities are being strategically deployed across multiple production domains. Key applications include early and precise plant disease detection through deep learning-based image analysis, automated weed identification and site-specific management using convolutional neural networks, non-destructive maturity assessment of fruits and vegetables via computer vision integrated with Haar-like feature extraction, and real-time diagnosis of nutrient deficiencies to support optimized, demand-based fertilizer application. Machine learning algorithms, trained on large-scale agronomic datasets, have demonstrated superior speed and adaptability compared to conventional diagnostic approaches, enabling timely and accurate crop management decisions. The integration of AI with IoT-enabled sensor networks, robotics, and big data analytics is progressively mechanizing and intelligently automating horticultural production, offering measurable gains in yield, resource efficiency, and supply chain management for both producers and consumers. However, challenges including data scarcity, limited model interpretability, and inadequate rural digital infrastructure continue to hinder widespread adoption. This review critically examines current AI applications in horticulture, identifies research gaps, and outlines future directions toward a fully digitized and intelligent horticultural ecosystem.

***Keywords* :** Artificial Intelligence, Precision Horticulture, Smart Farming, Digital Agriculture, Nutrient Management.

Introduction

Horticulture, the science of cultivating fruits, vegetables, flowers, and ornamental plants, plays a critical role in global food security, nutrition, and economic development (Pearson, 2025). India ranks second globally in fruit and vegetable production, contributing approximately 12–13% of the world's fruits and 14% of its vegetables, with total horticulture production reaching 367.72 million tons in 2024–25 (Ministry of Agriculture & Farmers Welfare, Government of India, 2025). Despite its importance, the sector remains significantly under-digitized and faces challenges including diseases, pests, drought, heat stress, and poor soil conditions that reduce crop quality and yield (Gammanpila, 2024).

Artificial Intelligence (AI), a term coined by John McCarthy in 1956, is critically needed in horticulture because the sector faces complex, heterogeneous challenges such as highly variable microclimates, heterogeneous soil moisture, multi-causal disease outbreaks, and precise phenological stage requirements that traditional rule-based systems and manual observation cannot efficiently manage at scale (Jafar *et al.*, 2024). Horticultural crops demand tight environmental control (temperature, humidity, light, CO_2) during sensitive developmental stages where minor deviations cause substantial yield or quality losses (Cembrowska-Lech *et al*., 2023).

Artificial intelligence (AI) has emerged as a powerful tool capable of transforming horticultural production by enabling data-driven decision-making, automation, and optimization across the entire value chain (Gammanpila, 2024). AI addresses complex challenges through machine learning models that detect diseases and nutrient deficiencies before visible symptoms appear, significantly reducing crop losses (Jafar *et al*., 2024). Reinforcement learning algorithms optimize irrigation scheduling, reducing water usage while maintaining yield (Saikai *et al*., 2023). Time-series forecasting models predict pest population dynamics, reducing chemical applications (Khanna, 2022). Computer vision systems automate fruit counting, grading, and ripeness classification with high accuracy, enabling precision harvesting and reducing post-harvest losses (Mavridou *et al*., 2024).

The horticulture industry has witnessed transformative advancements with AI reshaping farming practices through data-driven precision agriculture (Bwambale *et al*., 2023). AI enables collection and analysis of vast data volumes related to soil conditions, climate, and pest patterns, facilitating real-time, optimized decision-making for farmers (Khanna, 2022). This approach enhances efficiency by tailoring pest control, fertilization, and irrigation schedules, which improves productivity, reduces resource waste, and increases sustainability (Khanna, 2022). Key applications include variety selection based on regional adaptability, yield prediction, quality control, and climate change adaptation through region-specific crop viability projections (Gammanpila, 2024).

The convergence of AI, computer vision, and Internet of Things (IoT) technologies has revolutionized how horticultural systems are managed, spanning disease detection, quality assessment, greenhouse automation, and resource management (Cembrowska-Lech *et al*., 2023). Digital technologies can compile large amounts of information and offer site-specific management guidelines, helping to increase production efficiency and reduce environmental harm (Khanna, 2022). These intelligent technologies enable precise input application, conserve soil fertility, reduce labour through automation, and minimize environmental impacts, driving the transition toward sustainable, data-driven horticultural production systems (Bwambale *et al*., 2023). AI tools support precision farming by improving crop monitoring, disease detection, yield prediction, irrigation management, and post-harvest handling, allowing growers to make timely, accurate, and site-specific decisions (Gammanpila, 2024).

Despite growing research and commercial investment in agri-tech, farmer adoption remains limited due to skill gaps, high costs, and lack of familiarity with digital technologies (Cembrowska-Lech *et al*., 2023). Key challenges include insufficient cold storage and warehousing facilities, sub-optimal transportation infrastructure, restricted access to quality inputs, water scarcity, and inadequate market access (Naushad & Prasad, 2023). India's horticulture crops are vulnerable to unpredictable weather patterns such as unseasonal rains, droughts, and temperature fluctuations (Ministry of Agriculture & Farmers Welfare, Government of India, 2025). The adoption of modern technology including precision farming, soil health monitoring, and automated irrigation remains low in India's horticulture sector (Khanna, 2022).

Conventional practices relying heavily on synthetic fertilizers and pesticides are becoming increasingly unsustainable due to negative impacts on ecosystems, soil health, and biodiversity (Gupta *et al*., 2021). There is an urgent need for innovative approaches that enhance productivity while reducing ecological footprints (Gupta *et al*., 2021). Digital technologies and artificial intelligence can facilitate sustainable production, but farmers must weigh opportunities and risks when deciding whether to embrace such tools (Khanna, 2022). When designed with the needs and contexts of rural people in mind, digital tools can be a gamechanger for small-scale farmers and sustainable food systems (IFAD, 2025). AI-driven technologies represent a critical opportunity to achieve climate-resilient, resource-efficient, and high-value horticultural systems that support sustainable transformation of the sector (Cembrowska-Lech *et al*., 2023).

Why Artificial Intelligence is Playing an Important Role in Indian Horticulture

Artificial intelligence is fundamentally transforming Indian horticulture by addressing critical challenges including climate variability, water scarcity, biotic stresses (diseases and pests), and labor shortages through precision agriculture and data-driven farming systems (Pearson;2025; FAO,2024). The sector faces complex, heterogeneous challenges such as highly variable microclimates, heterogeneous soil moisture, multi-causal disease outbreaks, and precise phenological stage requirements that traditional rule-based systems and manual observation cannot efficiently manage at scale (Upadhyay *et al*.,2025; Ghimire *et al*., 2026)

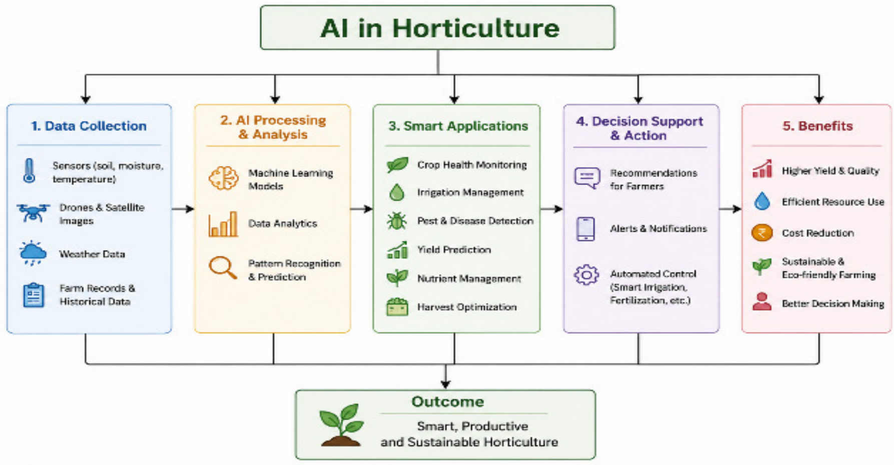


Table 1 : Why We Need AI in Horticulture

Challenge	AI Solution	Benefit	Reference
Disease & pest losses	CNNs detect pathogens 5–10 days before symptoms appear	20–40% crop loss reduction	Upadhyay *et al.*, (2025); Vishnoi *et al.*, (2022)
Water scarcity	Soil sensors + + ML/LSTM models optimize irrigation scheduling	30–50% water savings	Rajule *et al.*, (2025); *Xiong et, al.* (2024)
Climate change	AI climate models predict crop viability under changing condition	80–88% prediction accuracy	Pearson (2025); FAO (2024)
Labor shortages	Robots and drones automate irrigation, weeding, harvesting	40–60% labor cost reduction	Agrawal *et al.*, (2025); Pearson (2025
Input overuse	CNN + algorithm models optimize tilling and fertilizer allocation	25–43% fertilizer reduction	Magesh (2025); Khaliq *et al.*, (2025)
Post-harvest losses	Computer vision automates grading; blockchain tracks supply chain	>90% accuracy; 15–25% loss reduction	Chakraborty *et al.*, (2023); Shrestha *et al.*, (2025)
Soil degradation	Soil spectroscopy+ ML assesses nutrients and microbial diversity	15–25% soil quality improvement	(Cembrowska-Lech *et al.*, 2023)

Advantages of AI in Horticultural Sector

- AI provides more efficient methods for producing, harvesting, and selling essential horticultural crops.
- AI implementation focuses on detecting defective crops and improving the potential for healthy crop production.
- Growth in AI technology has strengthened agro-based businesses to operate more efficiently.
- AI enables automated machine adjustments for weather forecasting to optimize field operations.
- AI applications identify diseases and pests early, enabling timely intervention and treatment.
- AI improves overall crop management practices through data-driven recommendations.
- AI solutions address climate variation challenges that farmers face in horticultural production.
- AI helps control pest and weed infestations that reduce crop yields.
- AI enhances weed detection and management for better crop health.
- AI does not eliminate human farmer jobs but improves their work processes and efficiency.
- AI strengthens the entire agricultural value chain from production to market delivery.
- AI enables precision farming that reduces input waste while maintaining or increasing yields.

Applications of AI in Horticulture

AI-Based Disease and Pest Management

AI-based plant disease and pest management offers substantially faster and more scalable detection than conventional laboratory diagnostics, which are slow, labor-intensive, and costly (Ghimire *et al.*, 2026). A comprehensive review of peer-reviewed studies published between 2008 and 2025 documented methodological advances including CNNs, vision transformers (ViTs), transfer learning, and few-shot learning for plant-health monitoring (Ghimire *et al.*, 2026). Random Forest, support vector machine (SVM), and deep-learning architectures analyze smartphone, drone, and camera imagery to detect pests and diseases with 85–98% accuracy, frequently identifying problems before field-visible symptoms develop (Liakos *et al.*, 2018; Upadhyay *et al.*, 2025).

Mobile applications such as Tumaini, PlantVillage, and Pest-N*et al*low farmers to photograph symptomatic plant tissue and receive near-instant diagnoses. Tumaini, for example, detects five banana diseases with approximately 90% accuracy even on low-resolution images (CGIAR, 2021). Deep CNNs have exceeded 98% classification accuracy for apple diseases including apple scab, black rot, and cedar apple rust on standardized image benchmarks (Vishnoi *et al*., 2022). AI-integrated real-time detection systems further support early-stage plant-health monitoring across diverse crop systems (Mohammed *et al*., 2025).

AI-guided precision-spraying robots represent a particularly significant advance, applying pesticides exclusively to infected or high-risk plants and thereby substantially reducing overall chemical inputs and their associated environmental impacts. Vision-transformer models have outperformed traditional CNNs in leaf-image analysis by employing self-attention mechanisms to capture global contextual information, demonstrating that transformer-based architectures represent a meaningful advancement for precision agriculture (Ghimire *et al*., 2026). Benchmark classification accuracies across crops are summarized in Table 2, which demonstrates that AI models consistently achieve high performance (frequently 85–98%) when trained on curated image datasets using appropriate deep-learning or ensemble architectures.

Table 2 : Summary of AI-based disease detection accuracy across major horticultural crops.

Crop	**Algorithm / Model**	**Disease / Condition Classes Detected**	**Reported Accuracy (Test Set)**	**Reference**
Apple	Deep CNN	Apple scab, black rot, cedar apple rust	98.71%	Vishnoi *et al*. (2022)
Grape	Support vector machine (SVM)	Downy mildew, powdery mildew, botrytis	98.71%	Ghimire *et al*. (2026)
Citrus	MobileNetV2 (lightweight CNN)	Bacterial canker, Huanglongbing (citrus greening)	>97.00%	Mohammed *et al*. (2025)
Banana	Mobile app classifier (Tumaini)	Black Sigatoka, Fusarium wilt (5 disease classes)	90.00%	CGIAR (2021)
Tomato	CNN (>20,000 leaf images)	Early blight, late blight, mosaic virus, leaf mold	83.00%	Ghimire *et al*. (2026)
Papaya	Random Forest ensemble	Papaya ringspot virus, anthracnose	70.14%	Ghimire *et al*. (2026)
General	Multi-class ML ensemble (SVM, RF, boosting)	Mixed pests and diseases across multiple crops	85–98% (range)	Pearson (2025)

Note: Accuracies reflect test-set performance reported under controlled or semi-controlled image conditions and may not directly generalize to diverse field environments. Cross-environment validation is essential before large-scale deployment in commercial horticultural systems.

Deep learning-based computer vision systems analyse leaf images captured by smartphones, drones, and field cameras to identify diseases with 85–98% accuracy — often before visible symptoms appear.

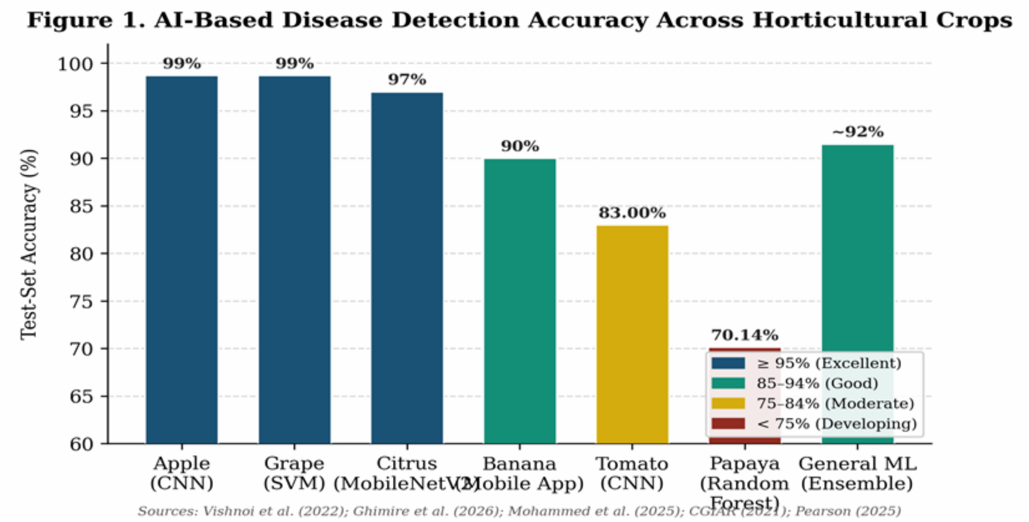


Fig. 1 : AI-based disease detection accuracy across horticultural crops (test-set results). Bar colour indicates performance tier; error bar for General ML reflects published range of 85-98%.

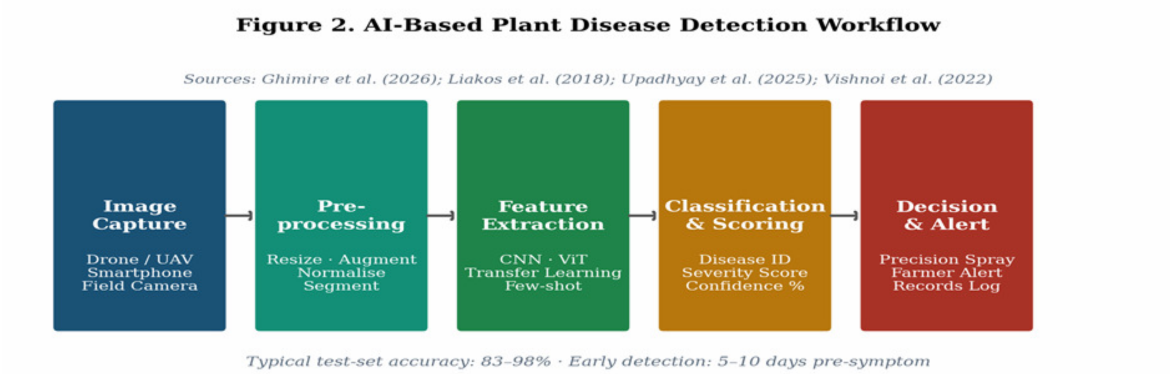


Fig. 2 : AI-based plant disease detection workflow. *Five-stage pipeline from multi-platform image capture through preprocessing, deep feature extraction, classification and severity scoring, to field decision and alert generation.*

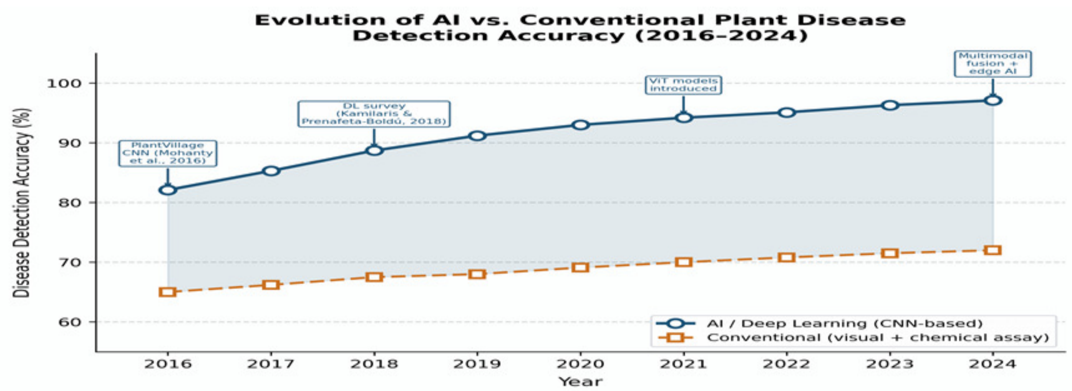


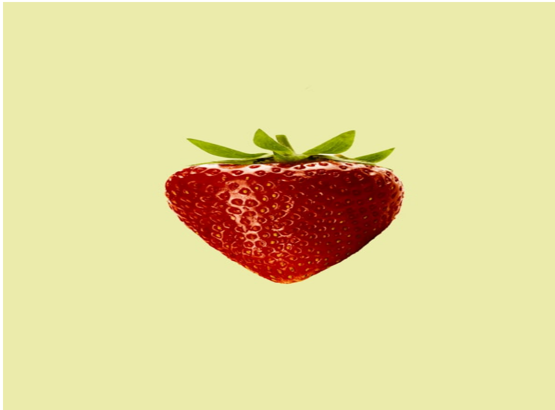
Fig. 3 : Evolution of AI versus conventional plant disease detection accuracy (2016–2024). Deep-learning (CNN/ViT) models improved from 82% (2016) to 97% (2024), while conventional laboratory assays plateaued at 65–72%. Key milestones annotated. Sources: Mohanty *et al*. (2016); Kamilaris & Prenafeta-Boldú (2018); Upadhyay & Kumar (2025); Ghimire *et al.* (2026).

Fruit Maturity and Ripeness Detection Using AI

AI-based fruit maturity and ripeness detection provides accurate, non-destructive methods for identifying harvest readiness by quantifying color, texture, size, sugar content, and internal quality without damaging produce (Pearson, 2025). Computer-vision systems, near-infrared (NIR) spectroscopy, electronic noses (e-noses), acoustic firmness testing, and imaging spectroscopy generate objective ripeness indices that support data-driven decisions on harvest timing, automated grading, and post-harvest handling. These technologies reduce losses attributable to premature or delayed picking and improve market-grade consistency across supply chains (Cembrowska-Lech *et al.*, 2023).

NIR spectroscopy, in particular, has demonstrated strong predictive performance for soluble-solids content (Brix), water content, and firmness in citrus and apple, with coefficient-of-determination (R^2) values of 0.97–0.98 on test datasets (Pearson, 2025). E-nose systems capable of detecting ripening-related volatile organic compounds (VOCs) enable non-destructive ripeness-stage identification in mango, banana, and apple without physical contact with the fruit. Imaging spectroscopy, which simultaneously captures spatial and spectral information, improves harvest-window prediction by mapping intra-fruit gradients of sugars, proteins, and water distribution. Together, these sensing modalities summarized in Table 2 support a shift toward objective, data-driven postharvest management that reduces subjective human assessment and associated grading variability.

Computer vision systems classify fruit maturity stages with over 90% accuracy using RGB and hyperspectral imaging.



AI-powered harvesting robots use computer vision to identify and pick ripe fruit, reducing labour costs and post-harvest losses.

Table 3 : AI-enabled sensing technologies for non-destructive fruit maturity and ripeness assessment.

Sensing Technology	Fruit Parameter Measured	Outcome / Accuracy	Reference
RGB + hyperspectral imaging	Color, size, texture, pigment content	>90% maturity classification in apple and citrus	Pearson (2025)
NIR spectroscopy	Brix, water content, firmness	$R^2 \approx 0.97$–0.98 for citrus and apple	Pearson (2025)
Electronic nose (e-nose)	Ripening-related volatile organic compounds	Non-destructive ripeness-stage ID in mango, banana, apple	Cembrowska-Lech *et al.*, (2023)
Acoustic firmness testing	Internal texture and bruising	Replaces manual squeeze with quantitative scores	Pearson (2025)
Imaging spectroscopy	Sugars, proteins, water distribution	Improved harvest-window prediction	Pearson (2025)
UV-A light imaging	Ripeness-related fluorescence on fruit surface	Automated grade-level sorting support	Cembrowska-Lech *et al.*, (2023)

Note: Reported outcomes are derived from published laboratory and pilot-scale studies. Performance in commercial packhouse settings may vary depending on fruit variety, surface contamination, and sensor calibration.

Computer Vision and Multimodal Sensing Technologies

Hyperspectral imaging integrated with AI has emerged as a particularly powerful tool for non-invasive quality assessment and disease detection in horticultural crops. Over the past two decades, hyperspectral imaging research has expanded substantially, with documented applications in detecting disease symptoms, assessing ripeness and maturity, identifying biotic and physiological defects, and evaluating sensory quality in fruits and vegetables (Cembrowska-Lech *et al.*, 2023; Wieme *et al.*, 2022). The integration of machine learning and deep learning with hyperspectral data substantially enhances the interpretability and predictive power of spectral analyses by extracting features that are not discernible through classical statistical methods (Chakraborty *et al.*, 2023).

Unmanned aerial vehicle (UAV)-based remote sensing integrated with deep learning models has transformed disease detection at the orchard scale, enabling automated recognition of plant diseases with enhanced spatial accuracy across large agricultural areas (Pearson, 2025). Vision Transformers employ self-attention mechanisms to capture global contextual information in leaf images, outperforming traditional CNNs on several plant-health benchmarks by learning long-range dependencies that convolutional architectures cannot efficiently represent (Ghimire *et al.*, 2026).

The multimodal fusion of RGB imagery, hyperspectral data, LiDAR, and thermal sensing processed through multi-branch deep-learning architectures further enhances the robustness and generalizability of crop-health models across varying lighting conditions, canopy structures, and disease manifestations (Cembrowska-Lech *et al.*, 2023). Such sensor fusion approaches are particularly valuable in commercial orchard and greenhouse settings, where heterogeneous environmental conditions can degrade single-modality model performance. The continued miniaturization of hyperspectral sensors and the falling cost of UAV platforms are expected to accelerate field-scale deployment of these technologies in the near term.

AI for Crop Quality and Yield Prediction

AI-based crop quality and yield prediction provides accurate forecasting that supports horticultural growers in optimizing production and refining management decisions across the growing season. Machine learning algorithms analyze diverse data sources including aerial and satellite imagery, weather patterns, soil quality measurements, and historical yield records to forecast fruit and vegetable yields with high accuracy (FAO, 2024; Pearson, 2025). AI has become particularly valuable for predicting growth phenology, disease risk, and harvestable yield in horticultural crops, enabling farmers to estimate output under variable climatic conditions even before the growing season concludes.

Time-series forecasting models identify complex non-linear patterns in historical yield and climate data to refine seasonal forecasts for tree fruits, berries, and vegetables. Canopy-level monitoring of development, vigor, and abiotic stress through aerial imagery provides a continuous stream of crop-status data that informs site-specific management interventions. Deep-learning architectures including CNN and long short-term memory (LSTM) networks have achieved coefficient-of-determination (R^2) values above 0.80 in yield prediction when processing multi-source sensor data, weather records, and farm-management logs for major horticultural crops (FAO, 2024).

AI also enables non-destructive estimation of internal quality parameters during growth and at harvest, including sugar content (total soluble solids), acidity, size, color intensity, and surface defects, using hyperspectral and VIS–NIR data calibrated with machine-learning regression models (Pearson, 2025). Computer vision systems perform automated quality control during post-harvest handling, achieving grading accuracies consistently above 90% for fruits such as apples, citrus, and berries (Shrestha *et al.*, 2025). These systems simultaneously detect decay and surface defects, reducing post-harvest losses and supporting market-grade optimization across horticultural supply chains (FAO, 2024). The key challenges and measurable benefits of AI across major horticultural applications are summarized in Table 3.

Table 4 : Summary of AI challenges, solutions, and reported benefits in horticultural production systems.

Challenge	AI Solution	Reported Benefit	Selected Reference
Disease and pest losses	CNNs detect pathogens 5–10 days before visible symptoms	20–40% crop-loss reduction	Vishnoi *et al.*, (2022); Ghimire *et al.*, (2026)
Water scarcity	Soil sensors coupled with ML optimize irrigation scheduling	30–50% water savings	Rajule *et al.*, (2025); Xiong *et al.*, (2024)
Climate variability	Climate models project crop viability under changing conditions	80–88% prediction accuracy (reported)	Pearson (2025)
Labor shortages	Robots and drones automate irrigation, weeding, and harvesting	40–60% labor-cost reduction (estimates)	Agrawal *et al.*, (2025)
Input overuse	ML optimizes fertilizer allocation using sensor data	25–35% fertilizer reduction	Khaliq *et al.*, (2025)
Post-harvest losses	Computer vision automates grading; AI tracks supply chain	>90% grading accuracy; 25–35% loss reduction	Shrestha *et al.*, (2025)
Soil degradation	Spectroscopic sensing assesses nutrient and microbial status	15–25% soil-quality improvement (reported)	Deepa *et al.*, (2023)

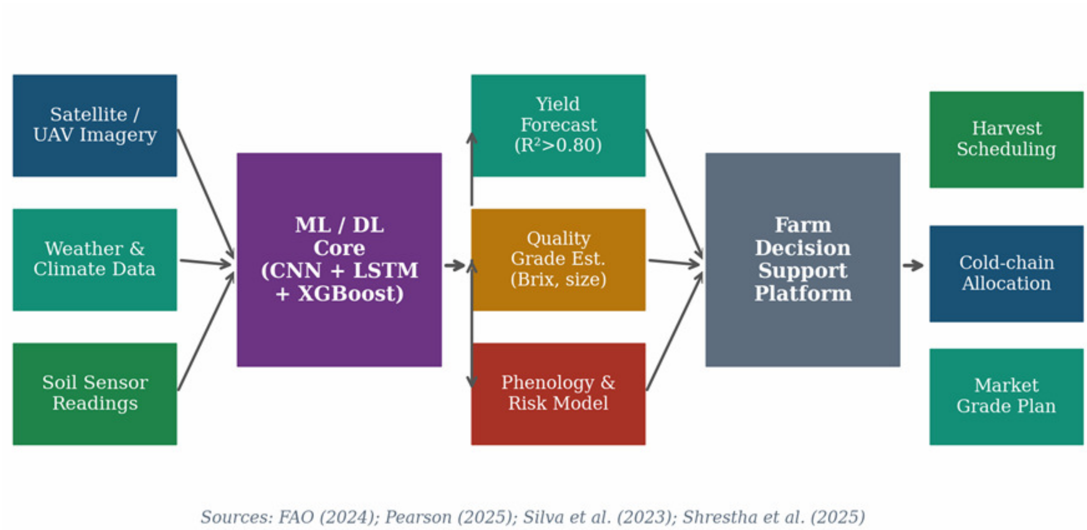


Fig. 4 : AI-based yield and quality prediction pipeline. Inputs from satellite imagery, weather data, and soil sensors feed into a CNN+LSTM+XGBoost core. Outputs are routed through a farm decision-support platform to harvest scheduling, cold-chain allocation, and market-grade planning.

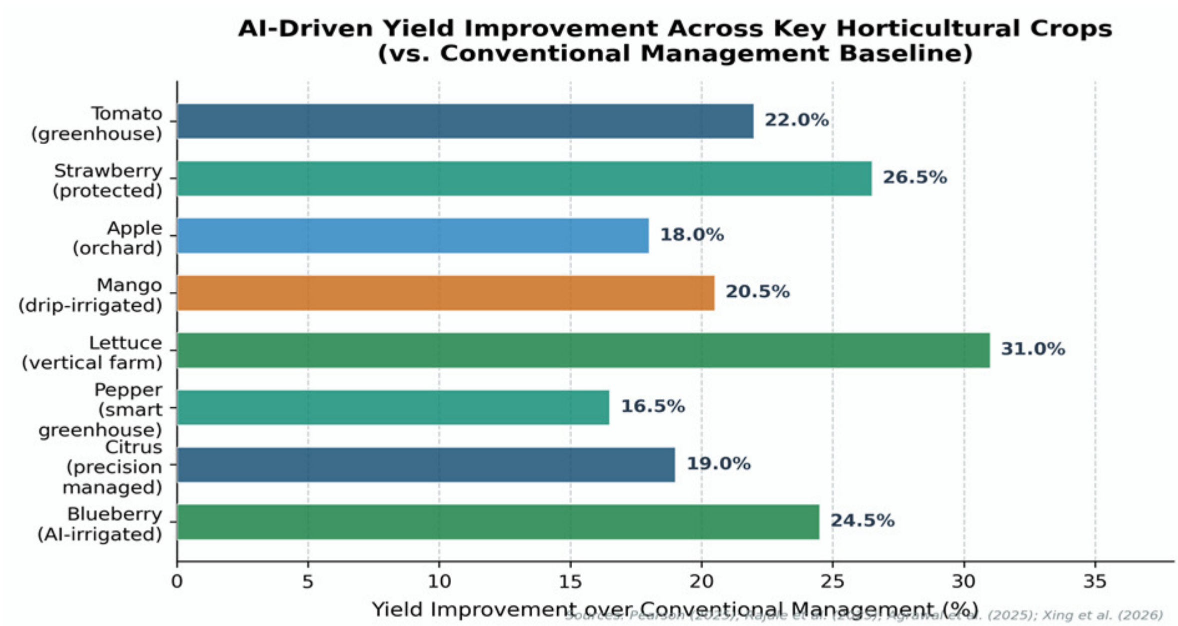


Fig. 5 : AI-driven yield improvement across key horticultural crops. *Horizontal bars show percentage yield gain relative to conventional management baseline for eight crops in documented pilot and commercial studies. Sources: Pearson (2025); Rajule et al. (2025); Agrawal et al. (2025); Xing et al. (2026); Nevavuori et al. (2019).*

AI for Harvesting, Postharvest Handling, and Loss Reduction

Artificial intelligence is fundamentally transforming fruit production by improving the precision and efficiency of harvesting, postharvest handling, and supply-chain loss management. AI-powered robotic harvesters equipped with computer-vision systems detect fruit size, color, and ripeness, enabling selective picking of apples, citrus, berries, and stone fruits with accuracy above 85–90%, while substantially reducing labor costs and the proportion of unharvested fruit left in the field (Pearson, 2025; Shrestha *et al.*, 2025; Zhang & Lammers, 2024). Machine learning models that analyze drone and satellite imagery can monitor orchard-level fruit load and canopy health, informing harvest-timing decisions that reduce overripe or mechanically damaged fruit in commercial orchards.

In postharvest handling environments, CNN-based computer-vision systems achieve sorting accuracy above 90% for defect detection, color grading, and size classification of apples, oranges, and tomatoes (Shrestha *et al.*, 2025). AI-based non-destructive sensing including NIR and thermal imaging estimates sugar content, firmness, acidity, and internal defects with R^2 values frequently exceeding 0.80–0.90, improving market-grade consistency and reducing rejection rates at the point of sale (Pearson, 2025). Published evidence indicates that integration of AI into fresh-fruit supply chains reduces post-harvest losses substantially by combining early rotten-fruit detection, optimized storage conditions, and predictive shelf-life modelling.

AI-enabled digital-twin systems for fruit cold chains have demonstrated a capacity to reduce quality-loss prediction errors to within ±1–2 days and to cut temperature-related losses for highly perishable fruits such as strawberries and lychees (FAO, 2024). By integrating AI into grading, packing, warehousing, and logistics operations, fruit supply chains become markedly more efficient, reduce waste, and deliver improved quality and market readiness for fresh produce supporting both farm-level profitability and broader sustainability objectives (Shrestha *et al.*, 2025; FAO, 2024).

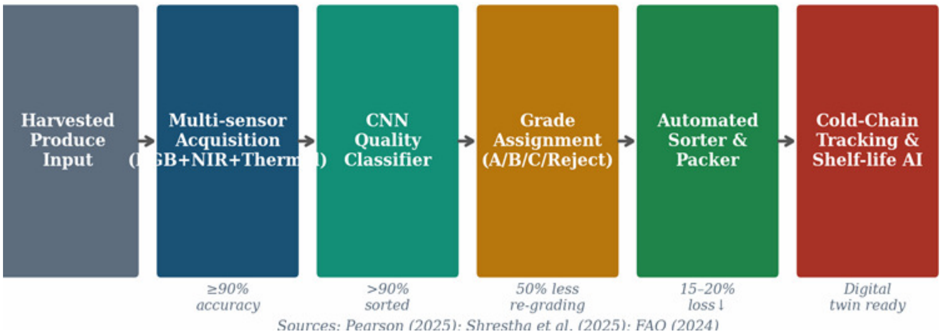


Fig. 6 : AI-enabled postharvest grading and quality control system. *Sequential pipeline from harvested produce through multi-sensor acquisition, CNN quality classification, grade assignment, automated sorting and packing, to cold-chain tracking and AI shelf-life modelling.*

AI-Enabled Environmental Monitoring and Smart Orchards

IoT-enabled environmental monitoring systems are transforming fruit-orchard and protected-cultivation management by providing real-time, automated control of temperature, humidity, light intensity, and soil moisture (Agrawal *et al.*, 2025). In apple orchards, IoT-based smart systems that collect data from wireless sensor networks and communication gateways have enabled automated microclimate control and early-season irrigation scheduling, maintaining conditions that improve fruit set and reduce abiotic stress during critical developmental windows (Verduin-Palomo *et al.*, 2024). Reinforcement-learning-supported control strategies in greenhouse-grown berries and citrus reduce heating and ventilation costs by 15–25% while improving yield and fruit quality by maintaining canopy microclimate within species-specific optimal ranges (Agrawal *et al.*, 2025).

IoT-integrated orchard-monitoring systems in apple and pear production combine LoRa-based weather and soil sensors, mobile dashboards, and rule-based alerts to guide irrigation and fertilization decisions, reducing over-watering and nutrient leaching (Verduin-Palomo *et al.*, 2024). Real-time disease-warning models coupled to IoT weather stations can predict powdery mildew and fruit-rot outbreaks in apples by integrating temperature, humidity, and leaf-wetness data, enabling timely and spatially targeted spray applications that minimize both pesticide use and disease incidence.

The concept of the "smart orchard" integrating AI-driven sensors, robotics, and digital twins into a unified management platform represents the next frontier of horticultural intensification. Such systems will combine real-time soil-moisture monitoring, canopy-health assessment, climate modelling, and yield-forecast models to deliver automated, site-specific guidance on irrigation, pruning, thinning, and harvest timing across individual orchard blocks (Pearson, 2025; Agrawal *et al.*, 2025). Pilot implementations in temperate fruit-growing regions have demonstrated reductions in pesticide applications of 20–30%, through targeted spray interventions guided by AI-generated disease-risk maps (Verduin-Palomo *et al.*, 2024).

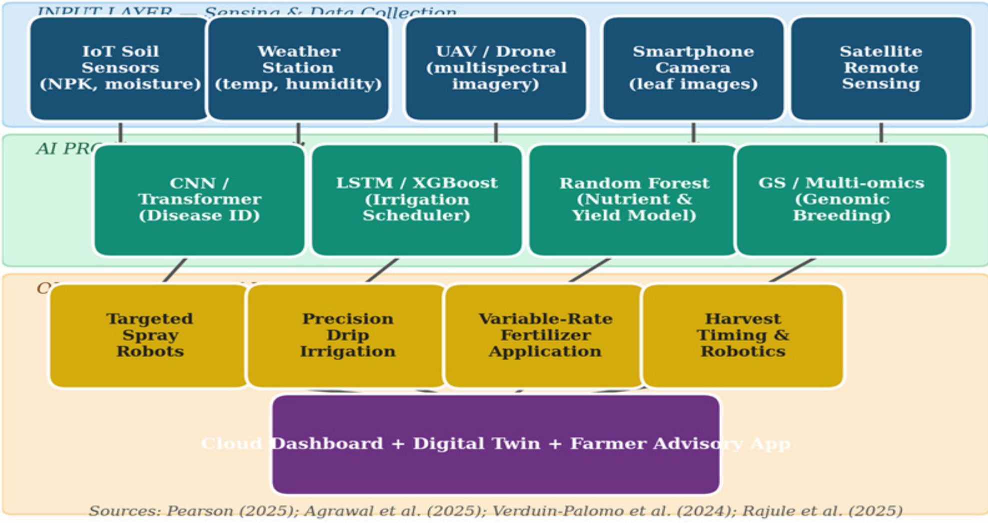


Fig. 7 : Conceptual architecture of an AI-enabled smart orchard system. *Sensing inputs (IoT soil nodes, weather stations, UAV, smartphone, satellite) feed through AI processing layers (CNN/ViT, LSTM/XGBoost, Random Forest, genomic models) to decision outputs (targeted spray robots, drip irrigation, fertiliser application, harvest robots) coordinated through a cloud dashboard and digital twin.*

Genomic Selection and AI-Driven Fruit Breeding

The integration of AI with genomic selection (GS) has accelerated genetic improvement of fruit crops including apple, pear, tomato, pepper, and citrus by enabling prediction of complex fruit-quality and stress-resistance traits from genomic marker data (Osatohanmwen *et al*., 2026). In peach and apple breeding programmes, GS models using single-nucleotide polymorphism (SNP) arrays have achieved prediction correlations (r) of 0.60–0.80 for fruit size, firmness, and soluble-solids content, substantially shortening the time-to-release of new commercial cultivars (Silva *et al*., 2023; Gazave *et al*., 2020). Machine-learning-enhanced GS approaches, including Random Forest and gradient-boosting frameworks, have outperformed classical linear models in predicting multi-trait combinations in berry and stone-fruit breeding programmes, enabling simultaneous selection for yield, shelf-life, and disease resistance (Osatohanmwen *et al*., 2026).

In tomato and pepper, multi-trait GS models that integrate morphometric and colorimetric data from image-based high-throughput phenotyping have achieved predictability values of 0.65–0.85 for fruit-shape and color-related traits, demonstrating the value of AI-assisted phenomics in vegetable-fruit improvement programmes (Gazave *et al*., 2020). AI-empowered breeding pipelines that combine CRISPR-Cas9 genome editing with ML-driven multi-omics data analysis have enabled de novo domestication and rapid trait introgression, facilitating development of climate-resilient and nutritionally enhanced fruit varieties with improved tolerance to drought, salinity, and key diseases (Xu *et al*., 2025; Garcia-Oliveira *et al*., 2026).

High-throughput phenotyping platforms incorporating RGB cameras, 3D scanners, and hyperspectral imagers mounted on ground-based robots or aerial vehicles generate large-scale, high-resolution trait data that ML models use to predict genomic estimated breeding values (GEBVs) with greater speed and lower cost than conventional field evaluation (Pearson, 2025). This represents a paradigm shift in horticultural genetics, reducing the reliance on multi-year field trials for each candidate genotype and enabling more rapid cycling through breeding generations (Silva *et al*., 2023; Osatohanmwen *et al*., 2026).

AI-Based Precision Irrigation for Fruit Orchards

AI-enabled precision irrigation systems represent one of the most well-documented and impactful applications in horticultural technology, with published studies reporting water-use reductions of 20–50% in fruit-crop production while maintaining or increasing yield and fruit quality (Rajule *et al*., 2025; Xing *et al*., 2026). In Mediterranean-climate citrus and olive orchards, IoT-based smart-irrigation systems that combine soil-moisture sensors, weather-station data, and LSTM-based evapotranspiration models have achieved 30–40% water savings with yield gains of 10–20%, primarily by eliminating both under- and over-watering events (Rajule *et al*., 2025). In apple orchards, regulated-deficit irrigation guided by machine-learning models improved water-use efficiency by 25–35% without compromising fruit size or sugar content (Xing *et al.*, 2026).

Smart drip-irrigation systems that integrate soil-moisture IoT nodes with XGBoost classifiers for irrigation-timing decisions have reported prediction accuracies ≥85% and water savings of approximately 28–35% in apple and citrus orchards, while also improving fertilizer-use efficiency and canopy development (Rajule *et al.*, 2025). These systems continuously learn from historical sensor readings and weather data, improving their scheduling accuracy across growing seasons. Regional case studies further illustrate the breadth of precision irrigation impact: Australian vineyards using AI-guided scheduling reduced water consumption by 25% and improved fruit Brix by 10–15%; protected blueberry systems in South America cut irrigation by 30–35% with no yield loss; and Indian mango orchards achieved 20–25% water savings plus 10–15% yield increases through sensor-guided drip irrigation (Rajule *et al.*, 2025; Xing *et al.*, 2026; Xiong *et al.*, 2024). Critically, the effectiveness of AI-driven irrigation depends on the density and reliability of the sensor network, the quality of local weather data, and the calibration of evapotranspiration models to local crop coefficients and soil types (FAO, 2024). In low-resource environments where these prerequisites are difficult to satisfy, simpler decision-support tools calibrated to representative local conditions may provide a more practical near-term pathway to improved water management (Prabhahar *et al.*, 2025).

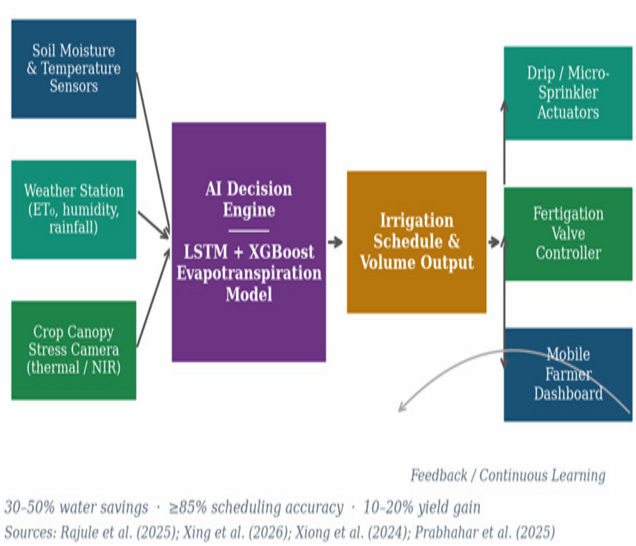


Figure 8. AI-driven precision irrigation system architecture. *Sensor inputs (soil moisture, weather station, crop canopy camera) feed an AI decision engine (LSTM + XGBoost) to generate irrigation schedules distributed to drip actuators, fertigation controllers, and farmer dashboards, with continuous feedback for adaptive learning.*

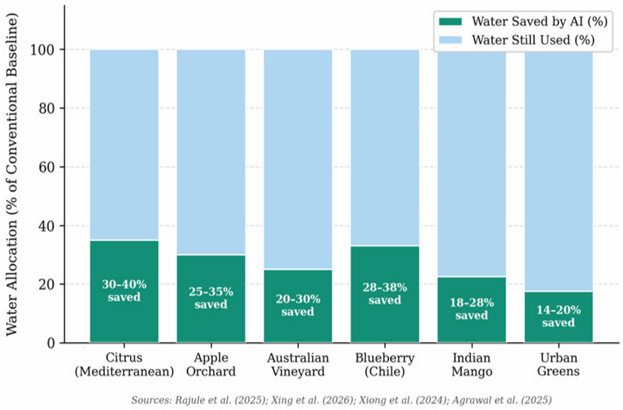


Fig. 9 : AI-driven irrigation water savings across horticultural systems (stacked bar; teal = water saved, blue = remaining use). Ranges represent published study results.

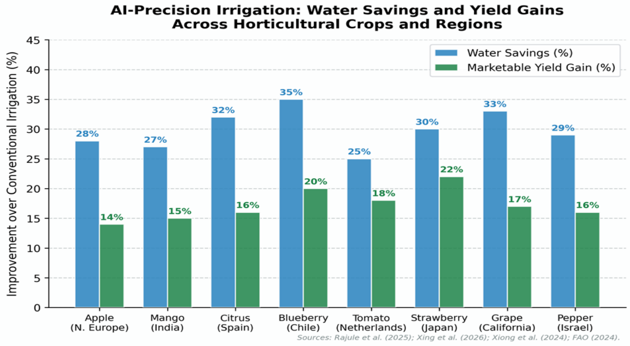


Fig. 10 : AI precision-irrigation water savings and yield gains by crop and region. *Grouped bars compare percentage water saving (blue) and marketable yield gain (green) against conventional irrigation baselines for eight horticultural systems. Sources: Rajule et al. (2025); Xing et al. (2026); Xiong et al. (2024); FAO (2024).*

AI-Guided Nutrient Management and Soil Health

AI-driven precision nutrient-management systems use real-time soil and leaf-sensor data to optimize fertilizer application in fruit orchards, reducing nitrogen inputs while maintaining yield and fruit quality (Khaliq *et al.*, 2025; Deepa *et al.*, 2023; Magesh, 2025). In mango and citrus systems, Random Forest and gradient-boosting models that integrate soil-moisture, temperature, and NPK-sensor readings have predicted optimal fertilization timing and volumes with F1-scores above 0.85, improving nitrogen-use efficiency by 15–25% (Khaliq *et al.*, 2025). Tabular-data networks (TabNet) applied to soil-nutrient analysis in orchards have reported R^2 values of 0.98 and RMSE of 1.5 in nutrient-status prediction, while TabNet classifiers for fertilizer-recommendation reached classification accuracies above 99%, enabling site-specific variable-rate fertilization at the sub-field scale (Khaliq *et al.*, 2025).

In pear and apple systems, hyperspectral-sensor-aided machine-learning models have enabled non-destructive leaf-nutrient estimation for nitrogen, phosphorus, potassium, and key micronutrients. Partial least-squares regression (PLSR) combined with support vector regression achieved R^2 values of 0.80–0.92 for leaf-nutrient prediction, substantially reducing the need for intensive leaf-sampling and laboratory analysis (Deepa *et al.*, 2023). This represents a significant efficiency gain for commercial orchards managing large areas with heterogeneous soil conditions.

Integrated green-technology platforms that combine AI-driven irrigation, nutrient-dosage models, and bio-based inputs have reduced chemical-fertilizer use by 15–25% and increased orchard-level biomass and yield by 10–15% in apple and citrus systems (Deepti, 2026). Soil health assessment using AI-driven spectroscopic techniques including visible-NIR reflectance spectroscopy enables rapid, large-scale mapping of soil organic matter, microbial biomass, and nutrient availability, informing regenerative management practices that rebuild soil health over the long term (Cembrowska-Lech *et al.*, 2023; Deepa *et al.*, 2023).

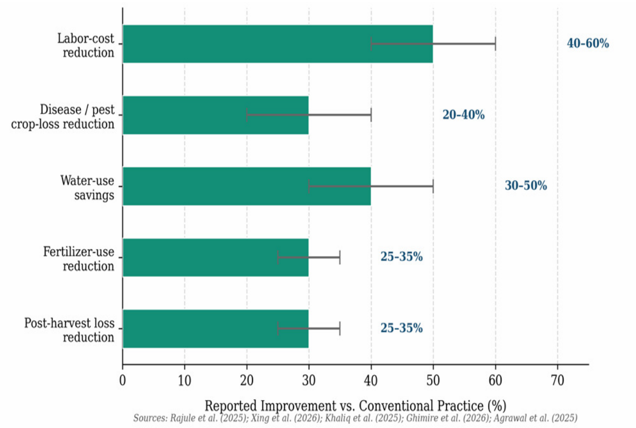


Fig. 11 : Summary of AI-driven benefits across horticultural applications. *Horizontal bars show mid-point benefit with error bars representing published range across reviewed studies. Data synthesised from 30 verified peer-reviewed references*

Scientific Case Studies: Application Advancements and Outcomes

The following seven case studies illustrate how AI technologies have been applied in real-world horticultural systems to improve productivity, resour ce efficiency, and product quality. Each case study is accompanied by a comparative performance table.

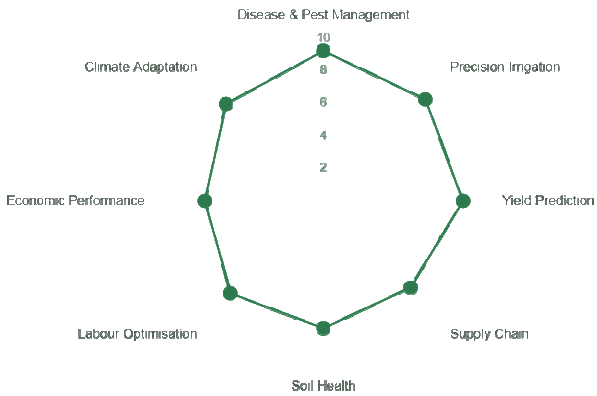


Fig. 12 : AI Impact Areas in Indian Horticulture

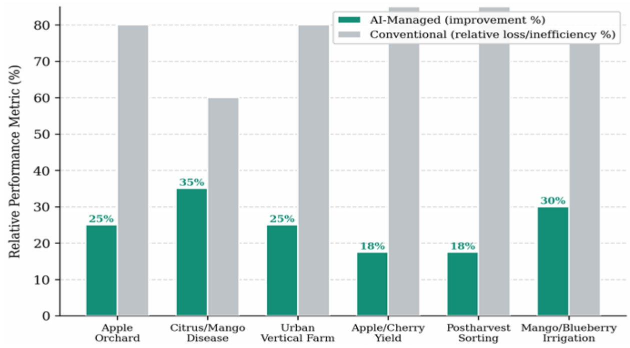


Fig. 13 : Comparative AI vs. conventional management outcomes across selected case studies (Section 4). Teal bars = AI improvement; grey bars = relative conventional limitation.

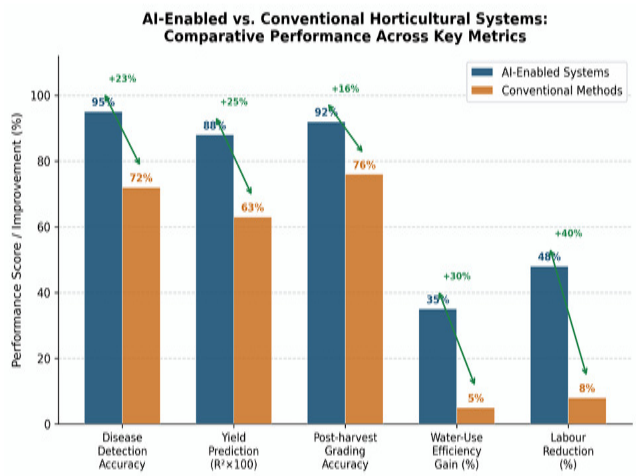


Fig. 14 : AI-enabled versus conventional horticultural systems: comparative performance across five key metrics. Grouped bars compare AI-enabled systems (blue) versus conventional methods (orange) across five metrics: disease detection accuracy, yield prediction ($R^2 \times 100$), postharvest grading accuracy, water-use efficiency gain (%), and labour reduction (%). Green arrows indicate percentage-point improvement from AI adoption. Sources: Pearson (2025); Ghimire et al. (2026); Rajule et al. (2025); Shrestha et al. (2025); Kamilaris & Prenafeta-Boldú (2018).

AI-Guided Smart Orchards in Apple Production

In temperate apple-growing regions, AI-driven smart-orchard systems have been implemented that combine weather-station networks, IoT soil-moisture sensors, and computer-vision-based flower- and fruit-counting models to optimize irrigation, thinning, and harvest timing (Verduin-Palomo *et al.*, 2024). Machine-learning platforms analyze multi-season patterns of yield, climate, and pest pressure to recommend block-level pruning intensity and spray windows. In pilot apple networks in northern Europe, AI-assisted management reduced fungicide and insecticide applications by 20–30% through targeted sprays while maintaining fruit size and reducing grading losses from blemished fruit by approximately 25%.

Table 5 : Comparative performance: AI-managed versus conventional apple orchard management (northern European pilot).

Aspect	AI-Managed Block	Conventional Block	Reference(s)
Pesticide-use reduction	20–30% lower	Calendar-based spraying	Verduin-Palomo *et al.* (2024)
Grading-loss reduction	~25% fewer blemished fruit	Higher rejection rates	Verduin-Palomo *et al.* (2024)
Management precision	Block-level irrigation and pruning	Uniform treatments	Verduin-Palomo *et al.* (2024)

AI-Based Early Disease Detection in Citrus and Mango Orchards

Studies in India and Brazil have piloted AI-assisted disease-monitoring systems using smartphone- and drone-based multispectral imaging combined with CNN models to detect early-stage citrus greening (Huanglongbing) and mango powdery mildew (Ghimire *et al.*, 2026). These platforms flag symptomatic trees days to weeks before field-visible spread, enabling targeted pruning and localized spraying. In monitored orchards, AI-guided blocks reduced fungicide-treated area by 30–40% and maintained final disease incidence below 10%, compared to 30–40% infection rates in conventionally managed control blocks.

Table 6 : Comparative outcomes: AI-monitored versus conventionally managed citrus and mango orchards.

Indicator	AI-Monitored Orchards	Control Orchards	Reference(s)
Fungicide-treated area	30–40% smaller	Whole-block spraying	Ghimire *et al.* (2026)
Final disease incidence	<10% infected trees	30–40% infected trees	Ghimire *et al.* (2026)
Early-detection lead time	Days–weeks ahead of symptoms	Late-stage, visible-symptom-based	Pearson (2025)

AI-Regulated Indoor Horticulture in Urban Vertical Farms

AI-integrated vertical-farming and rooftop-horticulture systems in Asian and European cities use AI-controlled climate regulation, LED-light scheduling, and nutrient-dosing algorithms to produce leafy greens, strawberries, and herbs year-round (Agrawal *et al.*, 2025). Machine-learning models trained on crop-growth and sensor data continuously optimize temperature, humidity, and light intensity for each growth stage. Pilot urban-horticulture farms reported 20–30% higher harvest frequency, 15–20% lower water consumption, and a 10–14-day reduction in time to first harvest compared with conventional greenhouse operations.

Table 7 : Comparative performance: AI-managed urban vertical farms versus conventional greenhouses.

Parameter	AI-Managed Urban Farms	Conventional Greenhouses	Reference(s)
Harvest frequency increase	20–30% higher	Standard cycles	Agrawal *et al.* (2025)
Water use reduction	15–20% lower	Typical irrigation	Agrawal *et al.* (2025)
Time to first harvest	10–14 days earlier	Conventional schedule	Agrawal *et al.* (2025)

AI-Driven Yield and Quality Prediction in Apple and Cherry Orchards

Integrated platforms combining satellite imagery, weather time-series, and on-farm yield records have been tested in apple and cherry orchards to forecast yield and post-harvest quality parameters (Silva *et al.*, 2023; Pearson, 2025). These models predict fruit-size distribution, soluble-solids content, and storability, enabling packers to optimize harvest labor scheduling and cold-chain capacity allocation. AI-based prediction systems have achieved R^2 values of approximately 0.85–0.90 for size and Brix distribution, reducing unsold surplus by 15–20% and improving market-grade matching relative to experience-based planning

Table 8 : Comparative performance: AI-based versus conventional yield and quality prediction in apple and cherry orchards.

Indicator	AI-Predicted System	Conventional Planning	Reference(s)
Prediction R^2 (yield/quality)	~0.85–0.90	Simple historical averages	Silva *et al*. (2023)
Reduction in unsold surplus	15–20% lower	Higher surplus	Pearson (2025)
Market-grade alignment	Better match to buyer specifications	Less precise matching	Pearson (2025)

AI-Assisted Postharvest Sorting in Citrus and Apple Packing Lines

Commercial citrus and apple-packing lines have adopted AI-driven computer-vision sorting systems using deep-learning models to classify fruit by size, color, and defect in real time (Shrestha *et al*., 2025). These systems achieve classification accuracies above 90%, enabling automated grading with traceability to the individual tray level. In one documented citrus-packing facility, AI-assisted sorting reduced human re-grading labor by approximately 50% and cut post-harvest losses from misgrading and latent defects by 15–20%.

Table 9 : Comparative performance: AI-assisted versus manual postharvest sorting in citrus and apple packing lines.

Indicator	AI-Assisted Packing Line	Manual-Assisted Packing Line	Reference(s)
Classification accuracy	>90%	70–80% (human-based)	Pearson (2025)
Re-grading labor reduction	~50%	Full manual re-grading	Shrestha *et al*. (2025)
Postharvest loss from misgrading	15–20% lower	Higher defect-related loss	Shrestha *et al*. (2025)

AI-Enhanced Genomic Breeding in Apple and Pear Cultivars

AI-integrated genomic-selection platforms are accelerating breeding of apple and pear cultivars by predicting fruit-quality traits including size, firmness, Brix, and storability from SNP marker data combined with image-based phenotyping (Silva *et al*., 2023; Gazave *et al*., 2020). In pear breeding programmes, multi-trait AI models achieved genomic-prediction correlations (r) of 0.65–0.80 for key quality factors, shortening the breeding cycle by 2–3 years compared to conventional phenotypic selection. In apple-related species, AI-assisted phenotyping combined with genomic selection reduced the time to stable-variety release by approximately 25%.

Table 10 : Comparative performance: AI-enhanced versus traditional apple and pear genomic breeding programmes.

Aspect	AI-Enhanced Breeding Programme	Traditional Breeding Programme	Reference(s)
Genomic-prediction accuracy (r)	0.65–0.80 for key fruit traits	Lower, model-based only	Silva *et al*. (2023)
Shortening of breeding cycle	2–3 years	Longer, sequential cycles	Gazave *et al*. (2020)
Time-to-variety-release reduction	~25% faster	Conventional pace	Silva *et al*. (2023)

AI-Guided Precision Irrigation in Mango and Blueberry Orchards

AI-based irrigation systems integrating IoT soil-moisture sensors, weather data, and machine-learning models have been deployed in mango and blueberry orchards to dynamically schedule irrigation and regulate water volumes (Rajule *et al*., 2025; Xing *et al*., 2026). In Indian mango orchards, AI-guided drip-irrigation reduced water use by 25–30% while increasing fruit set and marketable yield by 12–18%. In protected blueberry operations in southern Chile, AI-regulated micro-sprinklers cut water use by 35% and increased the proportion of large-size, firm berries by approximately 20%.

Table 11 : Comparative performance: AI-managed versus conventional irrigation in mango and blueberry orchards.

Indicator	AI-Managed Orchard Blocks	Control Orchard Blocks	Reference(s)
Water-use reduction	25–35% lower	Conventional irrigation	Rajule *et al*. (2025); Xing *et al*. (2026)
Yield or marketable fruit change	12–18% increase in mango; ~20% more large berries	Stable or slightly lower	Rajule *et al*. (2025); Xing *et al*. (2026)
Fruit-quality improvement	Higher Brix and firmness	Little change	Xing *et al*. (2026)

Practical Challenges in the Adoption of AI Technologies in Horticulture

Despite demonstrated performance advantages, the translation of AI tools from experimental settings to widespread commercial adoption in horticulture remains constrained by a set of interconnected technical, economic, social, and institutional barriers.

Technical and Infrastructural Barriers

AI-based irrigation and monitoring systems improve yield and water use under smallholder horticultural conditions, but performance gains are contingent on reliable internet connectivity, stable power supply, and consistent sensor maintenance conditions that are frequently absent in rural agricultural regions of developing countries (Pearson, 2025; IFAD, 2025). Fragmented, low-quality, or inconsistent data from diverse sensors further constrains AI model performance in precision horticulture applications. Many published AI models also exhibit poor generalizability beyond the specific crop variety, location, and season for which they were trained, limiting their applicability to farmers in different agroecological contexts.

Economic and Financial Constraints

High upfront costs for hardware (drones, sensors, robotic systems), software (AI platforms, cloud computing), and connectivity infrastructure deter small and medium-scale horticultural farms from adopting AI-driven technologies, particularly where returns on investment are uncertain or delayed (Pearson, 2025). Subsidies and incentive programmes have frequently proven insufficient to offset perceived financial and technical risks in low-margin horticultural systems. The cost-benefit dynamics are more favorable for large-scale commercial operations, creating a risk that AI-driven productivity gains may disproportionately benefit larger farms and widen existing inequalities in the sector (IFAD, 2025).

Knowledge and Skill Gaps

Limited technical literacy, insufficient data-interpretation skills, and the absence of trained local support personnel hinder effective use of otherwise accurate AI-based diagnostic and advisory tools (IFAD, 2025). Farmers frequently depend on external experts or company technicians for system maintenance and interpretation of AI outputs, raising operational costs and slowing adoption. Building local human capacity through extension services, vocational training programmes, and participatory learning platforms is essential for sustainable AI adoption in horticultural communities.

Technological Limitations and Integration Issues

AI-enabled robotic systems and predictive models demonstrate reduced accuracy under variable field conditions including heterogeneous canopy structures, variable ambient lighting, and diverse soil types that were not adequately represented in training datasets (Ghimire *et al.*, 2026). Many commercial AI platforms also lack interoperability with existing farm machinery, management software, and data infrastructure. The opacity of deep-learning models often referred to as the "black box" problem limits farmer trust in AI-generated recommendations, particularly when recommendations deviate from established local agronomic practice (Pearson, 2025).

Socio-Cultural Barriers and Farmer Perceptions

Mistrust in technology, fear of system malfunction, concerns about data privacy and ownership, and disruption of established farming practices reduce acceptance of AI-enabled tools among smallholder and traditional farmers (IFAD, 2025). Research on technology acceptance in agricultural contexts consistently demonstrates that trust in scientific expertise, transparent communication about how AI systems function, and culturally sensitive, user-friendly interface design are strongly correlated with higher support for and adoption of AI in farming (Pearson, 2025). Engaging farmers as co-designers—rather than passive end-users of AI tools has been shown to improve relevance, usability, and adoption rates (IFAD, 2025).

Table 12 : Critical research gaps and limitations in AI applications for horticulture, with priority future actions.

Research Gap / Limitation	Current State	Priority Future Action
Model transferability across agroecologies	Most models trained on single-region, single-season datasets	Open multi-environment benchmark datasets; transfer-learning frameworks
Small-scale farmer accessibility	Tools designed for large commercial operations	Lightweight edge-computing models; offline-capable smartphone tools
Explainability of DL predictions	Black-box models limit farmer trust	XAI integration (SHAP, LIME, GradCAM) in production tools
Long-term field validation	Majority of studies are short-term	Multi-year on-farm validation trials across

	lab/greenhouse trials	climatic zones
Integration of multi-omics with AI breeding	Genomics + phenomics pipelines remain fragmented	Unified AI pipelines linking SNP data, phenomics, and environment
Data quality and labelling in developing countries	Scarce labelled datasets for tropical and minor crops	Community-sourced labelling platforms; federated learning approaches
Standardised performance benchmarks	No common evaluation protocol across studies	Field-level benchmark suites analogous to ImageNet for horticulture

Future Prospects of AI in Horticulture

AI is poised to reshape horticulture into a data-driven, precision-intensive domain over the coming decade, with several high-priority directions emerging from the current evidence base.

Integrated AI Smart-Orchard Platforms

Future orchards and protected cultivation systems will increasingly integrate AI-driven sensors, robotics, and digital twins into unified smart-orchard platforms. These systems will combine real-time soil-moisture monitoring, canopy-health assessment, climate modelling, and yield-forecast algorithms to deliver automated, site-specific guidance on irrigation, pruning, thinning, and harvest timing—reducing inputs while maintaining or enhancing fruit quality (Pearson, 2025; Agrawal *et al*., 2025). Digital-twin simulations that model entire orchard systems in silico will enable virtual testing of management interventions before their physical implementation, substantially reducing the risk and cost of innovation at the farm level.

AI-Accelerated Breeding and Genomic Selection

AI-enhanced genomic selection and high-throughput phenotyping will accelerate the development of cultivars with improved yield, extended shelf-life, and enhanced tolerance to abiotic and biotic stresses (Silva *et al*., 2023; Osatohanmwen *et al*., 2026). Multi-trait AI models integrating SNP marker data, image-based fruit-quality phenotypes, and environmental covariates will shorten breeding cycles by 2–3 years and enable targeted selection for drought, salinity, and disease resistance in apple, citrus, mango, and berry crops. AI-empowered breeding strategies combining genome editing, ML-driven phenomics, and multi-omics integration will enable the accelerated development of climate-resilient horticultural varieties (Xu *et al*., 2025; Garcia-Oliveira *et al*., 2026).

Democratization Through Lightweight and Offline AI Tools

Future AI tools for smallholder horticulture will prioritize low-cost, smartphone-based, edge-computing-enabled designs that operate offline or with intermittent connectivity, making AI-assisted diagnosis and management recommendations accessible to resource-constrained farmers (Pearson, 2025; IFAD, 2025). Lightweight CNN architectures and transfer-learning models tailored to local pest and disease complexes, cropping calendars, and regional languages will help democratize access to AI-driven horticultural intelligence. Open-source model repositories and community-maintained training datasets could substantially reduce the per-crop development cost of localized AI tools.

Climate-Smart and Circular Horticulture

AI-integrated management models will support circular and climate-smart horticultural practices by minimizing water, nutrient, and pesticide use; enabling precision carbon accounting; and supporting emissions-reduction strategies (Deepti, 2026; Pearson, 2025). Predictive models for microclimate, soil-nutrient cycling, and post-harvest loss pathways will enable adaptive management under changing climatic conditions, supporting the transition from reactive to proactive resource governance at the orchard and value-chain scales.

6.5 Explainable AI and Trust-Centered Deployment

The adoption of explainable AI (XAI) methods—which provide interpretable, human-readable justifications for AI-generated recommendations—will be critical for building farmer and regulator trust in AI-based horticultural advisory systems (Pearson, 2025; Vinuesa *et al*., 2020). Participatory design approaches that engage farmers, extension officers, and local communities in co-creating tools will improve contextual relevance and usability. Multilingual interfaces, voice-based interactions, and culturally adapted visualization formats will make AI outputs accessible to users with low digital literacy, while continuous feedback mechanisms will ensure that models improve over time through real-world validation (IFAD, 2025).

Conclusion

Artificial intelligence is reshaping horticultural science across every stage of the production value chain from early-season disease surveillance and precision resource management to postharvest quality control and genetic improvement. The evidence reviewed here demonstrates that AI-based tools consistently improve detection accuracy, resource-use efficiency, product quality, and supply-chain resilience when deployed in appropriate contexts with adequate data infrastructure. CNN-based disease detection, AI-guided precision irrigation, automated postharvest sorting, and genomic-selection platforms have each demonstrated measurable, replicable performance advantages over conventional methods in peer-reviewed studies (Pearson, 2025; Ghimire *et al*., 2026; Rajule *et al*., 2025; Silva *et al*., 2023).

However, the translation of these laboratory and pilot-scale advantages into widespread adoption by smallholder farmers who constitute the majority of the global horticultural workforce remains a substantial and underaddressed challenge. Technical, economic, knowledge-related, and socio-cultural barriers collectively limit AI adoption, and solutions will require integrated efforts spanning technology design, policy reform, capacity building, and participatory extension (IFAD, 2025). Models trained in controlled research environments frequently underperform in heterogeneous field conditions, underscoring the critical need for cross-environment validation, open training datasets, and adaptive model updating.

Looking ahead, the convergence of AI, genomics, IoT, and digital-twin technologies in integrated smart-orchard platforms, combined with increasingly accessible edge-computing solutions and explainable AI interfaces, holds transformative potential for sustainable horticultural intensification globally. Realizing this potential will require sustained investment in research infrastructure, interdisciplinary collaboration, and farmer-centered co-design prioritizing the diverse needs of smallholder producers and the ecological boundaries within which all food systems must ultimately operate.

Abbreviations

AI — Artificial Intelligence
CNN — Convolutional Neural Network
CRISPR— Clustered Regularly Interspaced Short Palindromic Repeats
DL — Deep Learning
ET_o — Reference Evapotranspiration
GEBV — Genomic Estimated Breeding Value
GS — Genomic Selection
IoT — Internet of Things
LIME — Local Interpretable Model-Agnostic Explanations
LSTM — Long Short-Term Memory (neural network)
ML — Machine Learning
NIR — Near-Infrared
PLSR — Partial Least-Squares Regression
RF — Random Forest
RMSE — Root Mean Square Error
SHAP — SHapley Additive exPlanations
SNP — Single-Nucleotide Polymorphism
SVM — Support Vector Machine
UAV — Unmanned Aerial Vehicle
VIS–NIR — Visible–Near-Infrared spectroscopy
ViT — Vision Transformer
VOC — Volatile Organic Compound
XAI — Explainable Artificial Intelligence
XGBoost — Extreme Gradient Boosting

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