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Advancements of Artificial Intelligence in Horticulture: A Comprehensive Review

Mohit Paul[1], Gaurav Pandey[2] and Abdul Rub[3]

[1,2,3] Department of Computer Science and Information Technology, Sam Higginbottom University of Agriculture, Technology and Sciences, Prayagraj, India

[1]mohit90.paul@gmail.com, [2] gauravpandey161989@gmail.com, [3] abdulrub88@gmail.com

Abstract

Artificial Intelligence (AI) is rapidly transforming horticulture by introducing innovative solutions for phenotyping, cultivation practices, crop protection, postharvest handling, and breeding. Although significant advancements have been achieved in recent years, challenges such as scalability, affordability, limited farmer training, and the lack of transparency in AI models continue to restrict widespread adoption. Between 2019 and 2023, notable progress has been made, with systematic reviews of literature from databases such as Scopus, Web of Science, ScienceDirect, and IEEE Xplore highlighting promising applications. Out of 512 initially retrieved studies, 124 were shortlisted, and 72 were included after applying strict selection criteria. The findings suggest that AI holds immense potential in vision-based phenotyping, remote sensing, agricultural robotics, genomics integration, and the development of digital twin models. However, critical gaps remain in optimizing quality, diversifying datasets, improving farmer-oriented interpretability, and developing supportive policy frameworks. Emerging technologies such as Vision Transformers, neuro-symbolic AI, digital twins, and federated learning are shaping the future of AI-driven horticulture [2]. For equitable adoption, research must prioritize dataset standardization, participatory validation with farmers, cost-effective deployment strategies, and ethical governance. A practical roadmap for the future includes establishing dataset validation protocols, integrating hybrid AI with affordable robotics, and enabling ecosystem-wide adoption supported by regulatory and ethical frameworks.

Keywords: Artificial Intelligence, Horticulture, Precision Agriculture, Vision Transformers, Smart Farming

1. Introduction

Horticulture is a cornerstone of global nutrition security, rural livelihoods, and sustainable development. With rising climate variability, pest outbreaks, labor shortages, and supply chain disruptions, the sector is under pressure [1]. Artificial Intelligence (AI) provides data-driven solutions, shifting horticulture from intuition-based to evidence-based decision-making.

This review provides a critical assessment of AI in horticulture, integrating evidence from vegetable, fruit, and ornamental production systems. Unlike prior reviews, this paper emphasizes socio-economic impacts, farmer empowerment, and equitable adoption alongside technological progress.

2. Methodology

2.1 Literature Search Strategy

A systematic literature review was conducted following PRISMA guidelines. Search strings included "Artificial Intelligence in horticulture", "Machine learning in crop phenotyping", "Deep learning in fruit grading", and "Digital twins agriculture". Databases searched: Scopus, Web of Science, ScienceDirect, PubMed, and IEEE Xplore.

2.2 Inclusion Criteria

Studies were included if they:
• Focused on AI/ML/DL applications in horticulture
• Covered vegetables, fruits, and ornamentals
• Published between 2019-2023
• Provided empirical or validated methodologies
• Were published in English language

2.3 Data Extraction

Data extracted included: crop studied, AI technique, validation methods, performance metrics, socio-economic considerations, and adoption barriers.

2.4 PRISMA Flow

Articles retrieved: 512
Screened: 220
Shortlisted: 124
Final reviewed: 72

Records identified (n = 512)
↓
Records screened (n = 220)
↓
Full-text articles assessed (n = 124)
↓
Studies included in review (n = 72)

Figure 1. PRISMA Flow Diagram

3. Literature Review

AI adoption in horticulture accelerated post-2020. Key milestones included deep learning benchmarks for stress phenotyping (2021), IoT + AI integration for greenhouse monitoring (2022), operational greenhouse automation and the rise of Vision Transformers and federated learning frameworks (2023).

3.1 Phenotyping & Imaging

Recent advances demonstrate a growing shift toward lightweight and interpretable AI architectures for horticultural applications. Plant disease identification has benefited from transformer-based approaches such as the PMVT model, which integrates MobileViT and attention mechanisms for accurate disease detection on mobile devices.[11]

Hybrid frameworks like IEViT leverage inception modules with Vision Transformers, achieving high classification accuracy with minimal computational cost. Multitask ViT-based models such as PDLC-ViT have enabled simultaneous disease localization and severity scoring. Beyond visible spectrum imaging, UAV and multispectral-based systems such as SugarViT predict disease severity in sugar beet.

Studies in ornamentals show AI's potential in greenhouse risk prediction for tulips [2]. Collectively, these studies highlight a paradigm shift from single-task, data-intensive deep learning models toward resource-efficient, multi-task, and sensor-integrated frameworks.

3.2 Robotics & Automation

Robotics integrated with AI has advanced precision operations in harvesting, spraying, and weed management. Robotic harvesters equipped with soft grippers and deep learning–based vision systems demonstrate efficiency in delicate crops such as strawberries and apples.

Vision-guided spraying reduces chemical inputs by 60–80%. Autonomous vineyard robots with CNN and ViT-based detection achieve selective weeding. While effective, high cost and limited adaptability remain barriers, emphasizing the need for modular robotics and low-cost algorithms for smallholder adoption[13].

3.3 Socio-economic Adoption & Policy

Socio-economic challenges critically shape adoption. Proprietary AI models risk excluding smallholders who lack access to high-end devices and connectivity. Cooperative ownership models, shared service platforms, and subsidies are needed to ensure inclusivity.

Transparent, explainable AI systems can prevent farmer dependency on opaque algorithms. Policy frameworks emphasizing data rights, AI-linked insurance, and farmer-first governance are in early stages. Without intervention, risks of corporate monopolization persist. Therefore, adoption strategies must prioritize equity, affordability, and trust.

4. Current Applications

4.1 Phenotyping and Crop Monitoring

• Computer Vision: YOLOv5 and Mask R-CNN for fruit detection (tomato, mango)
• Vision Transformers (ViTs): Superior accuracy in disease classification under occlusion
• Stereo Imaging: 3D lettuce phenotyping [15]

4.2 Remote Sensing

• Satellite + UAV Fusion: Early disease detection in tomatoes
• LiDAR: Plant height and canopy volume assessment
• Thermal Sensors: Precision irrigation scheduling

4.3 Robotics and Smart Machinery

• Harvesting Robots: Strawberry and apple picking with soft robotics
• Selective Spraying: Reduces pesticide usage by 60–80%
• Weed Detection: Deep learning-enabled robots in vineyards

4.4 Omics and Breeding

• Deep Neural Networks: Genomic prediction for drought-tolerant varieties
• Transformer Models: Regulatory element design
• Metabolomics AI: Identifying flavor profiles in fruits

4.5 Postharvest Applications

• AI-based grading for apples, bananas, and mangoes
• Quality freshness detection in leafy vegetables
• Supply chain optimization using predictive analytics

Table 1. Applications of AI in Horticulture Across Crops

Domain	AI Technique	Crop Examples	Key Outcomes
Phenotyping	ViTs, CNNs	Tomato, Mango, Lettuce	Disease detection, stress phenotyping

Remote Sensing	UAV, LiDAR, Thermal	Tomato, Grapes, Cabbage	Disease prediction, irrigation management
Robotics	Deep learning + Robotics	Strawberry, Apple, Vineyard	Harvesting, spraying, weeding
Omics & Breeding	DNNGP, Transformer	Wheat, Rice, Vegetables	Genomic prediction, trait selection
Postharvest	ML + CV models	Apple, Mango, Leafy Greens	Sorting, grading, supply chain optimization

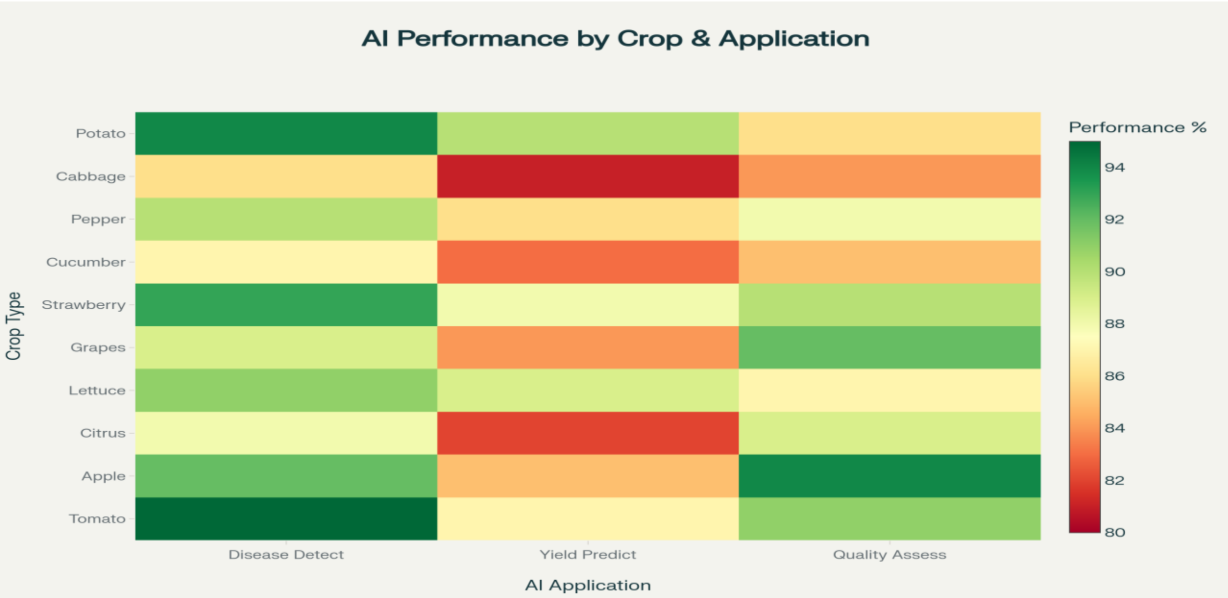

Fig 2. Crop-Specific AI Performance Matrix in Horticulture (2019-2023): Accuracy Across Disease Detection, Yield Prediction, and Quality Assessment [6]

5. Research Gaps and Challenges

• Quality vs. Quantity Trade-off: Most AI systems optimize for yield rather than quality attributes

• Data Limitations: Insufficient diverse, multi-location datasets for robust model training

• Farmer Empowerment: Lack of explainable, user-friendly interfaces for farmers

• Affordability: High costs exclude smallholder farmers from AI adoption

• Policy and Ethics: Inadequate governance frameworks for data rights and AI accountability

6. Emerging Technologies

6.1 Vision Transformers (ViTs)

Vision Transformers represent a paradigm shift in agricultural imaging, offering superior performance in:
• Multi-scale phenotyping with token-based approaches
• Robust disease detection under varying illumination conditions
• Multi-modal fusion of RGB, multispectral, and thermal data
• Advanced canopy analysis with occlusion handling capabilities

6.2 Neuro-Symbolic AI

Combining neural networks with symbolic reasoning enables:
• Transparent decision-making with explainable recommendations
• Integration of agronomic knowledge with machine learning
• Causal reasoning and "what-if" scenario analysis
• Adaptive learning from expert feedback and field outcomes[4]

6.3 Digital Twins

Digital twin technology provides comprehensive system modeling:
• Real-time crop-environment optimization
• Predictive modeling for growth simulation and yield forecasting
• Risk assessment and adaptation strategy development
• Resource optimization for input use efficiency

6.4 Federated Learning

Distributed learning approaches enable:
• Privacy-preserving model training across multiple farms
• Collaborative intelligence without data sharing
• Reduced bandwidth and storage requirements
• Farmer control over data sovereignty and usage

7. Implementation Roadmap

A three-phase roadmap is proposed for sustainable AI adoption in horticulture, addressing immediate needs, medium-term goals, and long-term vision.

Short-Term (0–12 months): Dataset standardization, AI-linked insurance

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Medium-Term (1–3 years): Hybrid AI, affordable robotics, cooperative models

↓

Long-Term (3–7 years): Integrated ecosystems, farmer data trusts, ethical governance

Figure 3. Implementation Roadmap for AI in Horticulture

7.1 Short-Term Priorities (0-12 months)

• Dataset standardization and validation protocols
• AI-linked insurance and risk management systems
• Performance assessment frameworks with multi-objective metrics
• Field validation under operational constraints

7.2 Medium-Term Goals (1-3 years)

• Development of hybrid neuro-symbolic AI systems
• Affordable robotics and modular automation solutions
• Cooperative ownership models and shared service platforms
• Training and support infrastructure for farmers

7.3 Long-Term Vision (3-7 years)

• Integrated AI ecosystems across the value chain
• Farmer-owned data trusts and governance structures
• Ethical frameworks and regulatory compliance
• Climate-resilient adaptation strategies

8. Case Studies

1. Tomato Leaf Disease Detection (India): CNN-based models achieving 96% accuracy in field conditions.
2. Strawberry Harvesting Robot (Japan): Soft robotics with computer vision reducing labor costs by 40%.
3. Grape Vineyard Monitoring (Italy): UAV-based multispectral imaging for precision viticulture
4. Apple Sorting (USA): AI-powered quality grading systems improving market premiums by 15%.
5. Parsley Freshness (Israel): Non-destructive quality assessment for export optimization

9. Economic and Social Implications

9.1 Economic Impact

AI adoption in horticulture demonstrates significant economic benefits:
• Input reduction: 20–40% reduction in water, fertilizer, and pesticide costs
• Yield increase: 15–25% improvement through precision management
• Market premium: Quality grading commands 10-20% price premiums
• Labor efficiency: Automation reduces labor requirements by 30-50%

9.2 Social Implications

• Digital divide challenges requiring inclusive technology design
• Need for farmer training and skill development programs
• Preservation of traditional knowledge alongside modern AI
• Cooperative models for equitable technology access

9.3 Policy Considerations

• Data rights and privacy protection frameworks
• Insurance mechanisms for AI-related risks
• Regulatory standards for AI validation in agriculture
• Support for smallholder farmer adoption

10. Conclusion

AI holds transformative potential in horticulture, from phenotyping and precision management to supply chain optimization. This comprehensive review of 72 recent studies (2019-2023) demonstrates significant advances in Vision Transformers, robotics integration, digital twins, and federated learning approaches [15].

However, successful adoption must prioritize farmer empowerment, affordability, explainability, and ethical governance. The three-phase implementation roadmap proposed herein emphasizes immediate dataset standardization, medium-term hybrid AI development with affordable robotics, and long-term ecosystem integration with farmer-centric governance.

Key recommendations include:
• Development of explainable AI systems tailored to farmer needs
• Implementation of cooperative ownership models for technology access
• Establishment of AI-linked insurance mechanisms for risk management

• Creation of policy frameworks ensuring data rights and ethical AI use

10.1 Future Outlook

By 2030, AI-driven horticulture should achieve:
• Resilient production systems adapted to climate variability
• Equitable access to AI technologies across farm sizes
• Transparent and trustworthy AI decision-making systems
• Sustainable intensification balancing productivity and environmental protection

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