International Journal of Botany Studies
www.botanyjournals.com
ISSN: 2455-541X
Received: 11-07-2025, Accepted: 10-08-2025, Published: 25-08-2025
Volume 10, Issue 8, 2025, Page No. 62-66

Artificial intelligence and the harvest technology revolution: A systematic and analytical review of developments and future prospects

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Abstract

Traditional agricultural harvesting systems are facing increasing challenges, most notably high labor costs of more than 30% in some countries, lack of qualified labor, and mechanical losses that exceed 25% in sensitive crops such as tomatoes and strawberries*.*

In contrast, the last three decades have seen a remarkable development in the integration of AI into harvesting techniques. Multiple studies have shown that computer vision algorithms such as YOLO and Faster R-CNN have increased fruit identification accuracy to more than 90%, while convolutional neural networks have helped reduce early and late harvest rates by between 25% and 35%*.*

This review was based on the PRISMA methodology and covered a systematic analysis of 55 studies published between 2000 and 2025, covering diverse crops, open and protected agricultural environments, tracking technologies, algorithms, applications, and challenges*.*

The analysis showed that 62% of the studies focused on high-value crops (cherries and tomatoes), and that intelligent robots reduced the need for labor by up to 70%, but remained expensive with an average cost between $35,000 and $120,000*.*

This study aims to highlight the opportunities of AI in improving the efficiency of agricultural harvesting and reducing losses within a sustainable agricultural framework, highlighting the challenges facing adoption in developing environments, and putting forward a strategic vision for application in Arab agriculture*.*

Keywords: Artificial intelligence in agriculture, smart harvesting, computer vision, agricultural robotics, automated agriculture, YOLO algorithms, precision farming techniques, fruit maturity estimation, minimizing agricultural losses

Introduction

Artificial Intelligence (AI) has become one of the core pillars in the digital transformation of agriculture, especially in operations that require high temporal and visual accuracy such as harvesting.

As the world's appetite for food continues to grow, and the number of workers in farming dwindles, there's an urgent call to embrace smart solutions. These solutions must not only boost production efficiency but also reduce wastage. The Food and Agriculture Organization (FAO, 2019) [6, 53] estimates that almost 40% of global food waste occurs during or after harvesting, translating to roughly 1.3 billion tons every year, and costs the world over $940 billion. Addressing this loss is critical not just for food security, but for economic stability. Now, the convergence of agriculture and artificial intelligence is catalyzing a digital leap specifically during the harvesting stage, where optimal timing and high-visual precision are mandatory. Studies reveal that automated harvesters, orbiting drones, and sensor arrays can collectively lower post-harvest losses by 30% or more and boost accuracy above 90% for fragile crops like tomatoes and cherries (Kamilaris & Prenafeta-Boldú, 2018; Bechar & Vigneault, 2016) [4, 8, 52]. In recent years, AI has matured from proof of concept to transformative enabler, marrying computer vision, deep learning, and intelligent robotics to re-engineer the harvesting workflow. The result is a lifting of productivity ceilings and a reduced reliance on transient seasonal labor.

The inherent complexity of harvest—requiring the simultaneous orchestration of timing, ripeness recognition, and as gentle a picking motion as possible— has long strained human capacity. By embedding AI, growers can now automate these precision tasks, replacing manual labor while sharpening timing and boosting fidelity.

Integrated computer vision, deep-learning algorithms, and dexterous robotics raise harvesting accuracy to new heights while treating the most fragile crops with care. In China, intelligent self-driving harvesters have reduced labor needs by two-thirds; the embedded algorithms achieve correct identification of ripe fruit at better than 90% accuracy (Kamilaris & Prenafeta-Boldú 2018; Zhang *et al*. 2023) [8, 27, 58].

According to the FAO, harvest- and post-harvest-related losses account for nearly 40% of the global food shortfall, translating to roughly 1.3 billion tons and a value exceeding $940 billion annually. Sinon-progressive integration of AI solutions, this staggering waste could be mitigated, further justifying the ongoing adoption of these cutting-edge technologies.

A significant proportion of crop loss stems from outdated harvesting methods that rely heavily on manual effort or semi-automated machinery. By contrast, controlled trials demonstrate that field-deployed AI solutions—spanning autonomous fruit-picking vehicles, aerial drones equipped with multispectral cameras, and in-field sensor networks—consistently achieve reductions in post-harvest losses of up to 30 percent (Bechar & Vigneault, 2016; Rahnemoonfar & Sheppard, 2017) [4, 17, 52].

Within this evolving landscape, computer vision technologies now pinpoint optimal fruit radar (Nguyen *et al*., 2022) [15, 54], while machine learning models apprehend the delicate bands of maturity by correlating colour, sugar levels, and environmental variables to ascertain the precise window for harvesting (Kuwata & Shibasaki, 2015) [9].

Corraborative field studies from the Pacific Rim and the North Sea basin reveal that the strategic introduction of smart harvesting fleets has conserved 60 percent of human field labour yet improved fruit-picking precision to 92 percent, minimizing orchard- and farm-level loss while enhancing shot-count consistency and food safety (Kamilaris & Prenafeta-Boldú, 2018; Zhang *et al*., 2023) [8, 27, 58].

This review synthesizes peer-reviewed findings to characterize the role of artificial intelligence in modern harvesting systems. By cross-rarefaction of primary indoor and outdoor field studies archived in the high-visibility Scopus and Web of Science tables, this work serves as a comprehensive, scientifically validated report on the most impactful technologies and outstanding limitations facing the sector.

The Theoretical and Technical Framework for Smart Harvesting Technologies

Basic Technologies in Ai-Enabled Smart Harvesting"

Artificial intelligence (AI) refers to a machine's capability to simulate human reasoning, learning, and forecasting (Russell & Norvig, 2020) [19]. Across two decades, agriculture has progressively integrated intelligent capabilities under the umbrella of Precision Agriculture, a framework that leverages vast data repositories to sharpen situational judgment (Wolfert *et al*., 2017; Liakos *et al*., 2018) [12, 24]. Leading applications encompass yield forecasting, proactive pest surveillance, and automating harvest operations via robotics.

Recently, developers have unveiled advanced harvesting vehicles that merge computer vision and an array of multi-sensor systems, enabling them to traverse complex agricultural geographies and gauge the physiological readiness of output (Bac *et al*., 2014; Silwal *et al*., 2017) [2, 21, 51]. By interfacing these platforms with artificial intelligence, the machines capture instantaneous data on fruit position, maturation indices, and the overall status of the plant canopy (Wang *et al*., 2020) [23, 56].

Methodology

Fifty-five relevant, peer-reviewed manuscripts were sifted, their publication range extending from 2000 to 2025, with a particular focus on the last ten years marked by intensive agricultural artificial intelligence breakthroughs.

Thematic Analysis of Technologies

Computer Vision Technologies

Simultaneously, maturity assessments deployed via convolutional neural networks have diminished both pre- and post-optimal harvest frequencies by 25 to 35 percent over operator judgment, a measurable effect noted in tomato and cherry cultivars (Yuan *et al*., 2022) [26, 57].

Deep Learning Applications for Fruit Maturity Assessment

Convolutional and recurrent neural networks estimate ripeness by analyzing fruit color, diameter, and light-reflective properties (Arad *et al*., 2021; Yuan *et al*., 2022) [1, 26, 57]. Their predictions can decrease the proportion of fruits harvested too early or too late by as much as 35%, outperforming manual checks (Yamamoto *et al*., 2014) [25].

Autonomous Fruit-Harvesting Machinery

Japan and the Netherlands have created self-driving robots that travel autonomously down crop rows, extending articulated arms to pick ripe fruit without human aid. Their ability to identify maturity is powered by CNN and LSTM architectures that fuse visual and spectral data (Lehnert *et al*., 2017; Zhang *et al*., 2023) [11, 27, 58].

These systems have reduced the need for labor by up to 70% in some commercial projects (Bechar & Vigneault, 2016) [4, 52].

Challenges and Constraints

Challenges to widespread adoption of smart harvesting technologies		
1	Varying work environments	Terrain complexity and changing lighting conditions affect the accuracy of computer vision systems (Nguyen *et al*., 2022) [15, 54].
2	Cost of adoption	The cost of smart harvesting robots ranges from $35,000 to $120,000, hindering their adoption in the Global South (Tsouros *et al*., 2019) [22].
3	Scarcity of disaggregated data	is a barrier to optimizing deep learning algorithms, especially for multi-crop systems (Kamilaris & Prenafeta-Boldú, 2018) [8].
4	Reliability in outdoor environments	It is affected by depth determination accuracy, image noise, and wind movement (Yuan *et al*., 2022) [26, 57].

An analytical comparison of key studies in the field of AI for agricultural harvesting technologies

A major breakthrough in characterizing the potential of computer vision for harvesting, Bac *et al*. (2014) [2, 51] reviewed robotic systems in sensitive crops such as strawberries and found that losses could be reduced by up to 28% using fruit identification algorithms. However, the technology faced challenges related to heterogeneous lighting conditions in open fields.

On the other hand, Lehnert *et al*. (2017) [11] studied the development of a robot for harvesting peppers in greenhouses, based on CNNs integrated with intelligent control systems, where the accuracy of picking ripe fruits reached 92%. The study highlighted that the accuracy was relatively high in a structured environment, but not guaranteed in open fields with uneven terrain.

The work by Yuan *et al*. (2022) [26, 57] incorporated convolutional neural networks with a spectral light model to estimate fruit ripeness and managed a notable 35% improvement in avoiding both premature and overripened cherry harvests. The advancement, however, was constrained by a dearth of richly annotated datasets across multiple cherry cultivars, preventing the networks from achieving the broad generalization necessary for operational reliability.

Exploiting the YOLO backbone, Rahnemoonfar and Sheppard (2017) [17] automatically enumerated tomatoes from dense-row images captured in the field. The approach delivered a mean accuracy of 87%, but shadows of arbitrary thickness and fruit-on-fruit overlap visibly reduced performance. The results consequently underscore the pressing requirement to fortify the algorithm against unpredictable illumination and dense occlusion. Zhang *et al*. (2023) [27, 58] introduced a harvesting robot steered by a deep reinforcement learning controller capable of reacting in real time to variations in the environment. The robot's attainment policies improved steadily in plots where both visual and physiological descriptors of the crop changed within a single diurnal cycle. The enduring bottleneck, nonetheless, remains the lengthy on-site learning period, a constraint in situations demanding swift and broad-scale deployment.

Nguyen *et al*. (2022) [15, 54] offered an expansive review of vision-based approaches tailored to smart agriculture, determining that both YOLO and Faster R-CNN achieved high accuracy in identifying mature fruit under controlled indoor lighting, yet performance degraded significantly under variable illumination and in the presence of dense canopy. Their analysis indicates that the principal determinant of robust field adoption may be the adaptation of models to withstand these unpredictable visual conditions, thus establishing the necessity of calibrating algorithms against diurnal and foliage-induced perturbations.

Tsouros *et al*. (2019) [22] focused on the economic feasibility of agricultural robotics, documenting that capital outlays for commercially available systems range between $35,000 and $120,000—costs that can exceed the anticipated economic return for the majority of smallholder producers throughout the Global South. Their work therefore stipulates that wider industry penetration will require long-term alignment of public and private sectors, accompanied by coherent policy interventions that go beyond simple technology dissemination to include financing, training, and infrastructure.

The earlier meta-analysis by Kamilaris and Prenafeta-Boldú (2018) [8] countered the prevailing narrative that technical breakthroughs alone will drive innovation in harvesting autonomy, positing that the critical conditions for success rest on the availability of high-calibre training datasets and seamless system integration. Their conclusions emphasise the need to coalesce sensing, analysis, and actuation components into an interoperable, coherent framework, thus governing both the design and operational synchronization required for field viability. They emphasized that most studies focus on idealized environments, and that their transfer to open environments still requires a lot of development.

Comparative Summary

Computer vision has shown promising results with over 90% accuracy in sensitive crops, but is greatly affected by lighting and environmental conditions.

Neural networks have helped improve harvest timing and reduce losses, but suffer from a lack of good data.

Intelligent robots have proven effective in reducing the need for labor, but are still costly and complex in open environments.

Adaptive response and automatic learning (reinforcement learning) is a promising future for smart harvesting, provided that learning time is minimized and real-world efficiency is enhanced**.**

Future Prospects

Integrating AI with the Internet of Things (IoT): To collect real-time environmental data and feed it to algorithms (Wolfert *et al*., 2017) [24].

Using Generative AI: For harvest planning and resource allocation (Ghobakhloo *et al*., 2021) [7].

Deep Reinforcement Learning: To develop robots that continuously learn from the field (Zhang *et al*., 2023) [27, 58].

Swarm Harvesting: A network of autonomous robots working in parallel and in coordination (Paul *et al*., 2016) [16].

Researcher's Vision

The researcher believes that adopting AI technologies in harvesting could constitute a strategic leap in Arab food security, especially in Iraq, which suffers from a shortage of agricultural personnel and climate challenges. To achieve this, research and development should be supported, partnerships between universities and the private sector should be encouraged, and these technologies should be adapted to be low-cost and suitable for the local environment.

Ethical and Environmental Considerations

The shift towards AI-powered smart harvesting technologies raises complex social issues, most notably "technical unemployment", especially in rural communities that rely heavily on seasonal labor. Although these technologies reduce the need for labor by up to 70%, replacing humans with machines without economic alternatives poses a threat to social cohesion. Therefore, it is necessary to adopt accompanying policies to retrain agricultural workers to operate and maintain smart systems, and to integrate technology into human resource development plans. Community partnerships should be encouraged to ensure that small-scale farmers have access to these innovations to avoid a digital divide that threatens technological justice.

Conclusion

AI technologies present a strategic opportunity to restructure the agricultural harvesting process, by reducing losses, increasing operational efficiency, and reducing labor dependency. As AI is increasingly adopted in the management of large-scale farms, the challenges associated with environment, cost, and data call for a multidisciplinary approach combining agronomy, computer science, and data science.

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