Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 47 No. 03
March 2026

Path Planning Algorithms for UAV Precision Agriculture: Methods, Gaps, and Future Directions

K.O. Oyedoja[1], Z.K. Adeyemo[2], D. O. Akande[2]

1. *Technology Education Department, Emmanuel Alayande University of Education, Oyo, Nigeria*
2. *Department of Electronic and Electrical Engineering, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.*

Abstract:

Unmanned Aerial Vehicles (UAVs) are increasingly central to precision agriculture, enabling high-resolution monitoring and targeted interventions across heterogeneous fields. Effective deployment hinges on path-planning algorithms that deliver safe, energy-aware trajectories under real farm constraints such as wind, irregular canopies, no-fly zones, moving machinery, and tight battery budgets. This paper surveys and synthesizes path-planning approaches for agricultural UAVs across four families: classical graph search such as heuristic and sampling, machine learning based, deep learning and others. The study maps each family to agricultural objectives such as coverage efficiency, safety, smoothness, constraints (endurance, turning limits, communication), and deployment readiness. The review identifies persistent gaps: heavy reliance on simulation, limited field validation in dynamic environments, weak coupling between planners and energy/endurance models, and scaling challenges for multi-UAV coordination. The study also highlights converging trends, hybrid DRL with sampling planners, heuristic coverage with agronomic constraints, perception-driven planning using lightweight vision models, and emerging use of Dynamic Mode Decomposition (DMD) for model reduction and onboard control. Finally, the study outlines a research agenda toward adaptive, field-validated planner that integrate energy modeling, multi-robot coordination, and onboard-deployable perception, providing a roadmap for robust autonomy in precision agriculture.

Keywords: Precision Agriculture; Path Planning; Machine Learning; Deep Reinforcement Learning (DRL); Unmanned Aerial Vehicle

1 Introduction

Unmanned Aerial Vehicles (UAVs) are now foundational tools in precision agriculture, enabling rapid, highresolution monitoring, and intervention across large and heterogeneous fields. By pairing flight autonomy with onboard sensing, UAVs support tasks such as crop health assessment, weed / pest scouting, and variable rate application. However, the practical value of these platforms is robust path planning, giving them the ability to calculate safe and efficient trajectories that maximize coverage and decision quality under real farm constraints (wind, terrain, no-fly zones, battery limits, and moving machinery/livestock) [1, 2, 3].

A broad spectrum of planning paradigms for agricultural UAVs has been investigated. Classical planners remain attractive for their predictability and completeness in structured or quasi-static settings. Heuristic methods, such as the Traveling Saleman Problem (TSP) and evolutionary and swarm optimizers, improve coverage efficiency and can incorporate multiple objectives such as energy, smoothness, and safety. In parallel, learning-based approaches that include deep reinforcement learning (DRL), recurrent models, and coupled perception planning networks offer adaptive policy optimization in dynamic and partially observable environments, with increasing evidence of gains in coverage, energy efficiency, and responsiveness to field conditions [4, 5, 6, 7].

Despite rapid progress, several research gaps persist. First, many demonstrations remain simulation heavy or limited to static/semi-controlled scenarios; translating to real farms with irregular canopies, heterogeneous row geometry, and moving obstacles is still challenging [8]. Second, energy- and endurance-sensitive planning under payload-dependent consumption profiles requires a tighter coupling between vehicle dynamics, mission constraints, and planning objectives [9]. Third, the multi-UAV case raises issues of coordination, communication, and collision avoidance that are not fully addressed by single-agent planners [7]. Finally, while perception-driven planning is advancing, producing lightweight models that run reliably on board for tasks like disease hotspot detection remains an active area, with recent work showing promise for efficient RGB pipelines and compact vision backbones [10].

Recent studies illustrate how these threads are converging toward field-ready solutions. On the learning side, DRL variants (DQN/DDQN with temporal models) have improved coverage path planning (CPP) performance and energy balance in agricultural mosaics; hybrids that combine sampling-based search with DRL further enhance global–local consistency [5, 6]. Heuristic formulations continue to be refined for agricultural tasks such as spot spraying and hedgerow /row crop coverage, often blending TSP-style visits with area coverage primitives and agronomic constraints [3]. For dynamic environments, motion planners integrating fuzzy potentials or multi-strategy fusion have reported safer, smoother trajectories under moving obstacles [4, 8]. Looking ahead, model reduction and data-driven system identification tools such as Dynamic Mode Decomposition (DMD) with control show potential to enable faster onboard-aware planning and control loops on resource-constrained UAVs, although their adoption in agricultural CPP is still emerging [11, 12].

This review synthesizes the state-of-the-art in UAV path planning for precision agriculture across four categories: classical, heuristic, machine learning, and deep reinforcement learning, highlighting their assumptions, metrics, and deployment readiness. The study emphasizes the gaps around robust field validation, energy/endurance modeling, scalable multi-UAV coordination, and lightweight perception planning pipelines, and the study propose future directions toward adaptive field-validated planners that can operate reliably in dynamic farm environments.

2 Fundamentals of Path Planning Algorithms

Autonomous navigation remains a cornerstone capability for unmanned aerial vehicles (UAVs) deployed in smart farming environments. The effectiveness of UAV operations particularly in field coverage, disease surveillance, and precision agriculture depends largely on the underlying path planning algorithm. These algorithms are tasked with computing feasible and efficient trajectories that ensure full coverage of designated areas while optimizing for energy, time, and safety constraints. In general, path planning algorithms can be categorized into four main classes as depicted in Figure 1: classical algorithms, heuristic-based approaches, machine learningbased models, and reinforcement learning or deep learning techniques.

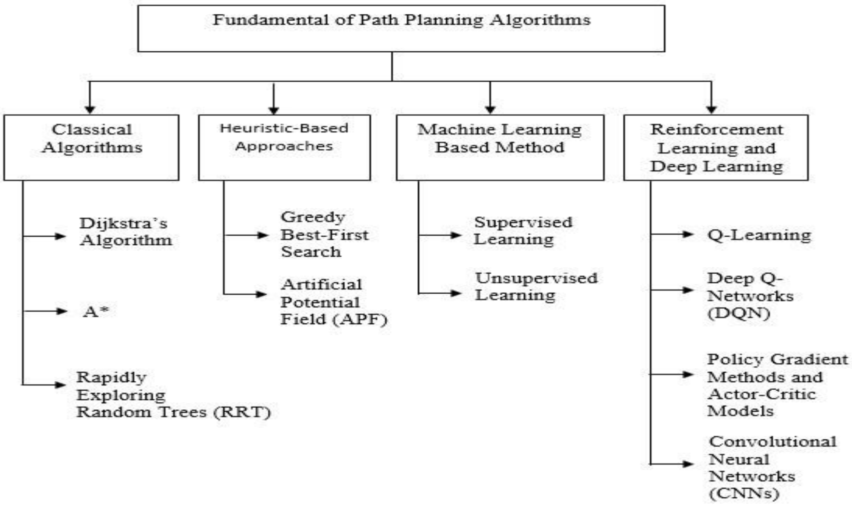

Figure 1: Overview of Path Planning Algorithm Categories for UAV Navigation in Smart Farming

2.1 Classical Algorithms

Classical path planning algorithms rely on deterministic graph-search principles, where the environment is discretized into a set of nodes V and edges E, forming a graph $G = (V,E)$. Each edge $e_{ij} \in E$ connecting nodes v_i and v_j has an associated traversal cost c_{ij}, typically representing Euclidean distance, energy consumption, or time.

2.1.1 Dijkstra's Algorithm

Dijkstra's algorithm computes the shortest path from a source node s to all other nodes in V by iteratively selecting the node with the minimum cumulative cost. The objective is to minimize:

$$\min d(v) = \sum_{(i,j)\in P} c_{ij} \tag{1}$$

where:

- $d(v)$ is the shortest path cost from s to node v
- P is the set of edges forming the path

The update rule for each neighbor v_j of the current node v_i is:

$$d(v_j) \leftarrow \min[d(v_j), d(v_i) + c_{ij}] \tag{2}$$

The algorithm terminates when all nodes are visited, ensuring global optimality under non-negative edge weights.

2.1.2 A* (A-Star) Algorithm

A* extends Dijkstra's approach by incorporating a heuristic function $h(v)$ that estimates the remaining cost from node v to the goal g. The evaluation function is:

$$f(v) = g(v) + h(v) \tag{3}$$

where:

- $g(v)$ = cumulative cost from the start node s to v
- $h(v)$ = admissible heuristic estimate of cost from v to g
- $f(v)$ = total estimated cost of the path through v

The search process prioritizes expanding nodes with the lowest $f(v)$, improving computational efficiency while preserving optimality if $h(v)$ is admissible (never overestimates).

2.1.3 Rapidly-Exploring Random Trees (RRT)

RRT is a sampling-based motion planning algorithm effective for high-dimensional spaces. Let $X \subset R^n$ be the configuration space with obstacle-free space X_{free} and obstacle space X_{obs}. The algorithm incrementally builds a tree T rooted at the start configuration x_{start}. At each iteration:

1. **Random Sampling:** Sample a random point $x_{rand} \in X_{free}$.

2. **Nearest Node Selection:**

$$x_{nearest} = \arg\min_{x\in T} \| x - x_{rand} \| \tag{4}$$

3. **Steer Towards Sample:**

$$x_{new} = x_{nearest} + \epsilon \frac{(x_{rand} - x_{nearest})}{\|x_{rand} - x_{nearest}\|} \tag{5}$$

where ϵ is the step size.

4. **Collision Check:** If the line segment from $x_{nearest}$ to x_{new} lies entirely in X_{free}, add x_{new} to T.

The process continues until x_{goal} is reached or a termination criterion is met. RRT guarantees probabilistic completeness but not optimality; extensions such as RRT* introduce rewiring steps to asymptotically approach optimal paths.

2.2 Heuristic-Based Approaches

Heuristic methods guide search or motion using problem-specific indicators to improve efficiency. In grid/graph settings, heuristics estimate distance-to-go; in continuous spaces, artificial potentials shape a navigation landscape whose negative gradient yields motion commands.

2.2.1 Greedy Best-First Search (GBFS)

Given a graph $G = (V,E)$ with nonnegative edge costs c_{ij} and a goal g, Greedy Best-First Search expands the frontier node that minimizes a heuristic $h(\cdot)$ estimating the remaining cost to the goal:

$$v^{\star} = \operatorname{argmin}_{v\in O} h(v), \tag{6}$$

where O is the open set. A common choice on grids is Euclidean or octile distance:

$$h(v) = \|p(v) - p(g)\|_2 \text{ or } h_{oct}(v) \tag{7}$$

with $p(\cdot)$ the position of the node. Unlike A*, GBFS does not accumulate the traveled cost $g(v)$ in its key, that is, $f(v) = h(v)$, which may yield faster searches, but can produce suboptimal paths. A smoothed path P can be obtained by post-processing with B-spline fitting:

$$\gamma(t) \;=\; \sum_{k=0}^{m} B_{k,m}(t)\, P_k, \qquad t \in [0,1] \quad , \tag{8}$$

where $B_{k,m}$ are Bernstein polynomials and P_k are control points sampled from P.

2.2.2 Artificial Potential Fields (APF)

Artificial Potential Fields (APF) are a widely adopted real-time motion planning technique that guide UAVs by simulating the environment as a virtual force field, attractive forces pull the agent toward its goal, while repulsive forces push it away from obstacles. This method is highly valued for its computational simplicity and intuitive representation, making it suitable for on-board implementation in dynamic environments [13, 14].

Despite its advantages, classical APF implementations suffer from well-known limitations such as local minima trapping and oscillatory behavior in cluttered settings. Recent research has focused on overcoming these drawbacks through hybrid or augmented approaches. [13] introduced a modified APF with virtual sub targets and collision risk assessment mechanisms, enabling smoother paths and reduced energy consumption in UAV flights. Similarly, [15] developed a Deflected Simulated Annealing–Adaptive Artificial Potential Field (DSA-AAPF) algorithm combining an adaptive APF with simulated annealing and leader-follower coordination, which improves obstacle evasion and supports robust multi-UAV formation maneuvers.

2.3 Machine Learning-Based Methods

Recent advances in machine learning (ML) enable UAVs to learn navigation policies directly from flight logs, annotated maps, or sensor data dramatically reducing reliance on handcrafted rules. These data-driven methods excel at generalizing across varied crop patterns and field conditions, particularly in precision agriculture where environmental heterogeneity is high [16, 17].

Supervised learning tools such as SVMs, decision trees, and random forests can learn from labeled datasets representing optimal UAV trajectories, aiding tasks like targeted spraying or weed detection. However, overfitting and limited coverage of environmental variations often limit their generalizability. Techniques such as domain adaptation or transfer learning are emerging as solutions to these limitations (adapting models from one crop soil type to another) [16].

Unsupervised methods, including clustering such as K-means and dimensionality reduction such as Principal Component Analysis (PCA), have been used for segmenting aerial imagery into management zones or detecting anomaly patches like disease hotspots. Self-organizing maps (SOMs) and autoencoders further aid feature discovery and anomaly detection in UAV data, guiding aerial inspection priorities in real time.

Emerging paradigms such as few-shot learning and meta-learning also show promise, allowing UAVs to rapidly adapt navigation strategies in new fields based on minimal examples. Moreover, sensor-fusion frameworks that integrate RGB, multispectral, LiDAR, and thermal inputs have elevated robustness in diverse agricultural contexts [16].

2.4 Reinforcement Learning and Deep Learning

In dynamic and partially observable environments such as agriculture farms with moving machinery, livestock, or variable weather, reinforcement learning (RL) and deep learning (DL) enable UAVs to learn optimal navigation policies through iterative interaction with the environment.

Deep reinforcement learning (DRL) methods have been demonstrated to enable adaptive path planning: for example, [18] apply DRL for efficient weed localization with UAVs, optimizing coverage while balancing energy constraints.

Comprehensive reviews categorize and map the use of RL and AI in farming across different tasks from crop monitoring to resource optimization, highlighting the emerging role of DQN, policy gradients, and actor–critic architectures in autonomous agricultural systems [19].

Deep Q-Networks (DQN), with powerful visual encoders such as CNNs, allow UAVs to make navigation decisions directly from raw RGB or multispectral imagery. Extensions like Double DQN and Dueling DQN improve training stability and efficiency. Policy gradient and actor–critic methods extend RL to continuous control spaces, critical for UAV flight with variable thrust, pitch, and yaw though applications in agriculture are still nascent.

Finally, multi-agent RL approaches and attention-based modules are beginning to support coordinated UAV–UGV teams and prioritize relevant environmental cues, paving the way for real-time, edge-deployable autonomous operations in remote farms [18].

3 Application of path planning in precision agriculture

Sonney et al, [21] integrates an improved A* with dynamic Q-learning to balance global path planning and local adaptability for UAV navigation in simulated agricultural fields with moving obstacles. The hybrid method improves efficiency in navigating dynamic environments but remains limited to simulation, lacking real-world validation.

Study by [22] shows a comparative analysis of parallel Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) was conducted for real-time UAV path planning in simulated missions. The results show PSO converges faster and produces smoother paths than GA, though the lack of agricultural field testing limits its applicability to precision farming.

The work by [23] applies Dubins curves integrated with RRT* for path planning of UAV-mounted manipulators in orchard-like environments. The method effectively handles turning constraints and obstacle avoidance in structured layouts, but it is restricted to static scenarios and has limited applicability in dynamic farm settings.

[24] approach involves combining A* search with Q-learning to addressing both static and dynamic agricultural field navigation. This enhances adaptability while maintaining efficient planning but has only been validated through simulations, without real-flight deployment.

[25] study leverages the Travelling Salesman Problem (TSP) framework with heuristic refinements for UAV coverage in obstacle-rich fields. The approach demonstrates high coverage efficiency in real UAV trials.

An improved A* algorithm is proposed by [26] for path optimization in industrial layouts, showing higher success rates and shorter paths compared to conventional methods. While promising, its lack of UAV-based testing makeing it agricultural adaptation uncertain.

The model by [27] fuses Bidirectional LSTM/GRU networks with a Double Deep Q-Network for UAV path planning over soybean raster maps. It achieves up to 22 percent better coverage with lower redundancy, yet field deployment and hardware integration remain untested.

A combination of Bi-directional LSTM-based DQN and U-Net segmentation is used by [28] for pest and disease spraying tasks in simulated environments. The method yields a 41.7 percent coverage improvement with precise segmentation, but it has yet to be validated in real agricultural conditions.

The study by [29] applies a double deep Q-Network for UAV coverage path planning under strict power and no-fly-zone constraints. It optimizes energy use while meeting coverage goals.

The study by [30] utilized counterfactual multi-agent reinforcement learning, which enables cooperative UAV teams for terrain monitoring. It adapts to varying team sizes and missions, but real-world agricultural testing is lacking.

Earlier [31] investigated multi-UAV data harvesting using MARL. The approach employed multi-agent reinforcement learning for decentralized coordination of UAVs in IoT sensor networks. While it demonstrates scalability in simulation, the absence of field implementation limits its current practical value.

The study by [32] further investigated DRL-Assisted UAV path planning with reward segmentation. A DRLbased planner using cumulative reward segmentation improves navigation in cluttered environments by avoiding local minima and accelerating learning. However, it has not been adapted to agricultural UAV operations.

Furthermore, other studies such as Adebayo et al. [33] present an integrated computer vision and control framework for sustainable precision agriculture, demonstrating how vision-based crop monitoring can be directly linked to actuation systems to optimize resource use and reduce waste. Ahmed et al. [34] focus on adaptive vision-guided robotic arm control for precision pruning in dynamic orchard environments, highlighting how real-time visual feedback and adaptive control strategies can handle occlusions and environmental variability for improved robustness. Complementing these works, Ghumman et al. [35] introduce AGRO, an autonomous AI rover platform that integrates perception, navigation, and task execution to enable scalable, continuous crop monitoring and data collection. Together, these studies illustrate the growing convergence of computer vision, control systems, and autonomy in precision agriculture, moving from perception-only solutions to fully integrated, field-deployable intelligent systems capable of sustainable and high-precision operations. Table 1 presents an overview of representative studies, highlighting their methodologies, datasets, strength and limitations.

4 Challenges and Future Directions

Despite the rapid development of UAV path planning algorithms, their deployment in precision agriculture faces several critical challenges that must be addressed to achieve scalable, autonomous and field-ready systems.

4.1 Real-World Deployment Gaps and Environmental Complexity

Many path planning algorithms are still validated primarily through simulations or controlled experiments, often oversimplifying real-world constraints such as irregular canopy geometry, dynamic obstacles, and fluctuating environmental conditions [2, 4, 8]. These factors significantly affect the accuracy of navigation and the reliability of the mission in operational farms. Future solutions should incorporate domain-aware modeling of terrain, soil variability, and crop density [3, 36], coupled with lightweight perception pipelines capable of dynamic scene reconstruction in adverse weather and lighting conditions [10, 14].

4.2 Energy and Endurance Constraints

Battery capacity remains a major limiting factor for UAV coverage, particularly in large-scale farms, and most algorithms do not adequately model energy consumption in relation to payload, wind conditions, and mission profiles [5, 37]. Incorporating physics-informed energy models [20] into planning algorithms could improve path feasibility assessments. Emerging research on solar-assisted UAVs also offers promising avenues to extend endurance [6, 11].

4.3 Multi-UAV Coordination and Swarm Intelligence

Although multi-agent reinforcement learning (MARL) and cooperative planning strategies have demonstrated potential [7, 38, 39], decentralized control of UAV fleets in dynamic farm environments remains a major challenge due to communication latency, collision avoidance complexities, and computational overhead. Future research should prioritize scalable decentralized frameworks leveraging mesh networking and co-optimization of aerial and ground robotic platforms for integrated farm operations [33, 35].

4.4 Lightweight and Adaptive AI Models

Deep reinforcement learning (DRL) and convolutional models have achieved impressive results in dynamic path planning [5, 9, 40], but their computational demands often limit the deployment of the onboard. Techniques such as model pruning, quantization, and knowledge distillation could enable edge-device autonomy without sacrificing performance [10, 16]. Additionally, few-shot and transfer learning approaches could improve adaptability across seasons, crop types, and geographies with minimal retraining [19].

4.5 Regulatory, Ethical, and Safety Barriers

The integration of UAVs into agricultural workflows faces regulatory challenges in the airspace, privacy concerns, and a lack of standardized safety protocols [1, 14]. Policies that define UAV flight corridors, licensing requirements, and data-sharing standards are essential for responsible adoption. Furthermore, integrating explainable AI (XAI) techniques into UAV decision systems could improve trust among farmers and regulators [33]

4.6 Future Research Directions

Future research on UAV-based path planning in precision agriculture should aim at developing adaptive and learning-based planning algorithms capable of handling the dynamic and uncertain nature of agricultural environments. Traditional approaches such as A* and Dijkstra's algorithm, while computationally efficient, often assume static environments and can struggle with real-time replanning in the presence of wind disturbances, moving machinery, or growth-related occlusions. Integrating sampling-based planners such as RRT* with online optimization techniques and receding-horizon control can enable UAVs to dynamically adjust trajectories on the fly. Furthermore, graph-based deep learning methods, including Graph Neural Networks (GNNs), can be leveraged to represent farm topology and learn optimal navigation policies from historical flight data. Reinforcement learning (RL), particularly deep RL methods like PPO and DDPG, could be explored to allow UAVs to learn energy-efficient routes that maximize coverage under time and battery constraints.

Another promising avenue is the deployment of multi-UAV cooperative systems for large-scale farms, where task allocation can be formulated as an optimization problem and solved using Mixed-Integer Linear Programming (MILP) or decentralized Multi-Agent Reinforcement Learning (MARL). These approaches enable collaborative coverage, swarm-level coordination, and robust collision avoidance through distributed consensus algorithms. Future research should also incorporate energy-aware planning, considering battery health, charging cycles, and even renewable energy sources such as solar-powered UAVs for persistent operations. Finally, a key step toward real-world applicability will be rigorous field validation, including testing under seasonal variability, adverse weather conditions, and edge-case scenarios to ensure robust, generalizable performance before deployment in production-scale smart farming systems.

Table 1: UAV Path Planning Research Overview

Category	**Study**	**Algorithm**	**Dataset / Scenario**	**Strengths**	**Limitations**
Classical Algorithms	[21]	Improved A* + Dynamic QLearning Hybrid (IEEE Access, 2023)	Simulated agricultural fields with moving obstacles	Efficient balance of global planning and local adaptability	Simulation only; no real-world validation
	[22]	Parallel GA vs. PSO for real-time path planning (IEEE Trans. Ind. Inf., 2012)	Simulated UAV missions	PSO converges faster and yields smoother paths than GA	Lacks testing in agricultural environments
	[23]	Dubins-RRT* for orchardlike layouts (Computers & Electronics in Agriculture, 2019)	Picking manipulator paths in orchards	Accommodates turning constraints; good obstacle avoidance	Limited to static and structured layouts
Heuristic-Based App	[24]	A*-Q-Learning Hybrid Planner (IEEE Access, 2023)	Simulated dynamic and static fields	Combines planning efficiency with adaptAbility	Simulation-tested; lacks real-flight data
	[25]	TSP-based coverage with heuristic refinement (arXiv,	Field patches with obstacles	High in-field coverage efficacy	Not peer-reviewed yet

		2024)			
	[26]	Improved A* for industrial paths (Robotics & Autonomous Systems, 2018)	Industrial environment layouts	Higher success rate and shorter path Lengths	Not tested on UAVs
ML-Based Methods	[27]	BiLG-D3QN (Deep RL + Bi-LSTM/GRU) (MDPI Agriculture, 2025)	Soybean raster maps	Up to 22% better coverage; low redundancy	Sim-only; needs field validation
	[28]	BL-DQN + U-Net segmentation (MDPI Agronomy, 2024)	Pest/disease spraying simulations	41.7% improved coverage; efficient segmentation	Simulation-only; no hardware trial
	[29]	Path planning under power constraints with DDQN (arXiv, 2020)	CPP tasks with no-fly zones	Balances energy use and coverage goals	Not peer-reviewed
Reinforcement Lear	[30]	Multi-UAV Informative Deep LearningPath Planning with Counterfactual DRL (arXiv, 2023)	Terrain monitoring, multi-UAV	Learns cooperative behavior; adaptable to team size	Simulation-only
	[31]	Multi-UAV data harvesting using MARL (arXiv, 2020)	IoT sensor networks in city/field Clutterded environments	Decentralized, scalable coordination	Preprint; no real testing
	[32]	DRL-assisted UAV path planning with reward segmentation (IEEE OJVT, 2024)		Avoids local minima; faster learning	Not yet implemented in agriculture
Others	[33]	A hybrid computer vision pipeline integrating image segmentation (CNN-based), feature extraction, and a rule-based control algorithm for actuation.	Tested on real-world agricultural fields with heterogeneous crop growth conditions, capturing RGB images under varying lighting and weather scenarios.	Strong emphasis on sustainability, linking perception to control for closed-loop operation. Demonstrates robustness in noisy agricultural environments and highlights potential for	Focused on a single crop type; scalability to multi-crop or multiseason deployment not fully validated. Details on computational efficiency and model generalization are limited.

			resourceefficient farming.	
[34]	Adaptive control strategy combining deep learningbased fruit tree branch detection with feedback-driven robotic arm trajectory planning. Incorporates dynamic adjustment to compensate for occlusions and tree motion (wind)	Conducted in an orchard setting with dynamically changing tree branches, leveraging real-time RGB-D vision data.	Strong adaptability to environmental variability and occlusion, making it field-ready. Combines perception with control in a closed loop for precision pruning.	Performance may degrade in low-light conditions or for very dense canopies. Requires high-quality, calibrated depth sensors and relatively expensive robotic hardware.
[35]	End-to-end autonomous rover system combining SLAM (Simultaneous Localization and Mapping), object detection (CNN-based), and task planning modules for crop monitoring and navigation.	Tested in open-field agricultural environments with varying terrain and obstacles, demonstrating mobility and perception under real-world conditions.	Fully autonomous, integrating navigation, perception, and decision-making into a single platform. Scalable solution for large farms and continuous monitoring.	Hardware complexity and cost may limit adoption by smallholder farmers. Energy efficiency and long-term deployment challenges (battery life, maintenance) are not fully addressed.

References

[1] I. Anam, N. Kassim, and M. A. Hannan, "A systematic review of UAV and AI integration for targeted crop management," *Computers and Electronics in Agriculture Reports*, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2772375524002521

[2] D. Debnath, F. Vanegas, J. Sandino, A. F. Hawary, and F. Gonzalez, "A Review of UAV Path-Planning Algorithms and Obstacle Avoidance Methods for Remote Sensing Applications," *Remote Sensing*, vol. 16, no. 21, p. 4019, 2024.

[3] S. V´elez, D. Rodr´ıguez-Lin˜´an, and A. Gonz´alez, "Integrated framework for multipurpose UAV Path Planning in hedgerow-based precision agriculture," *Crop Protection*, 2025.

[4] M. H. Garibeh, M. Alam, and A. R. Al-Ali, "A real-time fuzzy motion planning system for unmanned aerial vehicles in dynamic 3D space," *Applied Soft Computing*, vol. 153, 110035, 2024.

[5] H. Fu *et al.*, "Research on Path Planning of Agricultural UAV Based on Improved Deep Reinforcement Learning," *Agronomy*, vol. 14, no. 11, 2669, 2024.

[6] G. G. R. de Castro *et al.*, "Adaptive Path Planning for Fusing RRT and Deep Reinforcement Learning in an Agriculture Dynamic Environment," *Agriculture*, vol. 13, no. 2, 354, 2023.

[7] J. Wang, X. Shu, and X. Deng, "Multi-UAV Area Coverage Track Planning Based on the Voronoi Graph," *Applied Sciences*, vol. 14, no. 17, 7844, 2024.

[8] L. Xu *et al.*, "Dynamic path planning of UAV with least inflection point optimization in complex environments," *Scientific Reports*, 2025.

[9] R. van Essen, E. van Henten, and G. Kootstra, "UAV-based path planning for efficient localization of nonuniformly distributed weeds using deep reinforcement learning," *Computers and Electronics in Agriculture*, 2025.

[10] Y. Lyu *et al.*, "UAV-Based RGB Imaging and Lightweight Deep Learning for Downy Mildew Detection in Kimchi Cabbage," *Remote Sensing*, vol. 17, no. 14, 2388, 2025.

[11] A. K. Al-Jiboory, M. Shahbakhti, and M. Abdelkhalik, "Adaptive quadrotor control using windowed Dynamic Mode Decomposition with control," *Aerospace Science and Technology*, 2024.

[12] M. J. Colbrook, S. Olver, and A. Townsend, "The multiverse of dynamic mode decomposition algorithms," *Applied and Computational Harmonic Analysis*, 2024.

[13] G. Hao *et al.*, "UAV Path Planning Based on Improved Artificial Potential Field Method," *Aerospace*, vol. 10, no. 6, Art. 562, 2023.

[14] A. Merei *et al.*, "A Survey of Obstacle Detection and Avoidance Methods for UAVs," *Remote Sensing*, vol. 9, no. 3, p. 203, 2025.

[15] B. Ma, Y. Ji, and L. Fang, "A Multi-UAV Formation Obstacle Avoidance Method Combined with Improved Simulated Annealing and an Adaptive Artificial Potential Field," *Drones*, vol. 9, no. 6, Art. 390, 2025.

[16] J. Agrawal and M. Y. Arafat, "Transforming Farming: A Review of AI-Powered UAV Technologies in Precision Agriculture," *Drones*, vol. 8, no. 11, Art. 664, 2024. :contentReference[oaicite:11]index=11

[17] D. Debnath, F. Vanegas, J. Sandino, A. F. Hawary, and F. Gonzalez, "A Review of UAV Path-Planning Algorithms and Obstacle Avoidance Methods for Remote Sensing Applications," *Remote Sensing*, vol. 16, no. 21, Art. 4019, 2024. :contentReference[oaicite:12]index=12

[18] R. van Essen, E. van Henten, and G. Kootstra, "UAV-based path planning for efficient localization of nonuniformly distributed weeds using deep reinforcement learning," *Computers and Electronics in Agriculture*, 2025. :contentReference[oaicite:13]index=13

[19] M. Padhiary, "A comprehensive review of machine learning and AI vision techniques in farming," *Computers and Electronics in Agriculture Reports*, 2024. :contentReference[oaicite:14]index=14

[20] Fu, H. (2025). Path Planning for Agricultural UAVs Based on Deep Reinforcement Learning and Energy Consumption Constraints Using Bi-LSTM and Bi-GRU Networks. *Agriculture*, 15(9), Article 943. MDPI.

[21] Sonny, A., Yeduri, S. R., & Cenkeramaddi, L. R. (2023). Q-learning-based unmanned aerial vehicle path planning with dynamic obstacle avoidance. *Applied Soft Computing*, 147, 110773.

[22] Roberge, V., Tarbouchi, M., & Labont´e, G. (2013). Comparison of Parallel Genetic Algorithm and Particle

Swarm Optimization for Real-Time UAV Path Planning. *IEEE Transactions on Industrial Informatics*, 9(1), 132–141. https://doi.org/10.1109/TII.2012.2198665

[23] Yang, Y., Leeghim, H., & Kim, D. (2022). Dubins path-oriented rapidly exploring random tree* for threedimensional path planning of unmanned aerial vehicles. *Electronics*, 11(15), 2338.

[24] Li, D., Yin, W., Wong, W. E., Jian, M., & Chau, M. (2021). Quality-oriented hybrid path

planning based on A* and Q-learning for unmanned aerial vehicle. *IEEE Access*, 10, 7664–7674.

[25] Plessen, M. (2025). Path planning for spot spraying with UAVs combining TSP and area coverages. *Smart Agricultural Technology*, 100965.

[26] Fu, B., Chen, L., Zhou, Y., Zheng, D., Wei, Z., Dai, J., & Pan, H. (2018). An improved A* algorithm for the industrial robot path planning with high success rate and short length. *Robotics and Autonomous Systems*, 106, 26–37. https://doi.org/10.1016/j.robot.2018.04.007

[27] Fu, H., Li, Z., Zhang, W., Feng, Y., Zhu, L., Long, Y., & Li, J. (2025). Path Planning for Agricultural UAVs Based on Deep Reinforcement Learning and Energy Consumption Constraints. *Agriculture*, 15(9), 943.

[28] Fu, H., Li, Z., Zhang, W., Feng, Y., Zhu, L., Fang, X., & Li, J. (2024). Research on path planning of agricultural UAV based on improved deep reinforcement learning. *Agronomy*, 14(11), 2669.

[29] Theile, M., Bayerlein, H., Nai, R., Gesbert, D., & Caccamo, M. (2020, October). UAV coverage path planning under varying power constraints using deep reinforcement learning. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (pp. 1444–1449). IEEE.

[30] Puente-Castro, A., Rivero, D., Pedrosa, E., Pereira, A., Lau, N., & Fernandez-Blanco, E. (2024). Q-learning based system for path planning with unmanned aerial vehicles swarms in obstacle environments. *Expert Systems with Applications*, 235, 121240.

[31] Liao, J., Sun, C., Zheng, J., Guo, X., Song, T., Ren, J., ... & Wang, S. (2024, June). Multi-agent reinforcement learning for backscattering data collection in multi-UAV IoT. In *ICC 2024 – IEEE International Conference on Communications* (pp. 1576–1581). IEEE.

[32] Wang, Z., Ng, S. X., & Mohammed, E. H. (2024). Deep reinforcement learning assisted UAV path planning relying on cumulative reward mode and region segmentation. *IEEE Open Journal of Vehicular Technology*, 5, 737–751.

[33] Adebayo, S., Aworinde, H. O., Ojerinde, S. A., Oyedoja, K. O., Adeniyi, A. E., Olanloye, O. D., ... & Das, A. (2025). Computer Vision and Control Algorithm for Sustainable and Precision Agriculture. *SN Computer Science*, 6(4), 362.

[34] Ahmed, D., Imran, B. M., Churuvija, M., & Karkee, M. (2025). Adaptive Vision-Guided Robotic Arm Control for Precision Pruning in Dynamic Orchard Environments. *arXiv preprint arXiv:2504.07309*.

[35] Ghumman, S., Di Troia, F., Andreopoulos, W., Stamp, M., & Rai, S. (2025). AGRO: An Autonomous AI Rover for Precision Agriculture. *arXiv preprint arXiv:2505.01200*.

[36] Del-Coco, M., Leo, M., & Carcagnì, P. (2024). Machine learning for smart irrigation in agriculture: How far along are we?. *Information*, *15*(6), 306.

[37] Elmeseiry, N., Alshaer, N., & Ismail, T. (2021). A detailed survey and future directions of unmanned aerial vehicles (uavs) with potential applications. *Aerospace*, *8*(12), 363.

[38] Hou, Y., Zhao, J., Zhang, R., Cheng, X., & Yang, L. (2023). UAV swarm cooperative target search: A multi-agent reinforcement learning approach. *IEEE Transactions on Intelligent Vehicles*, *9*(1), 568-578.

[39] Ekechi, C. C., Elfouly, T., Alouani, A., & Khattab, T. (2025). A survey on UAV control with multi-agent reinforcement learning. *Drones*, *9*(7), 484.

[40] Lei, X., Zhang, Z., & Dong, P. (2018). Dynamic path planning of unknown environment based on deep reinforcement learning. *Journal of Robotics*, *2018*(1), 5781591.