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Robotics and Computer Vision in Precision Agriculture: A Systematic Review of Applications and Technology Readiness

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ABSTRACT

This paper presents a systematic review of recent advances in robotics and computer vision for precision agriculture, analyzing 118 peer-reviewed articles published between 2021 and 2025. The objective of this study is to synthesize technological advances, identify research gaps, and provide a roadmap for the maturity of agricultural robotics. The research contribution involves the development of a structured taxonomy that links agricultural tasks, robotic platforms, sensing modalities, and AI models, the proposal of a conceptual pipeline from perception to actuation, and a critical synthesis of technology readiness levels (TRLs) and methodological biases. Searches were conducted in specialized engineering and robotics databases, following PRISMA guidelines and applying explicit inclusion and exclusion criteria. From 440 initial records, 118 articles were selected after screening. Extracted variables included platform configurations (aerial, ground, and fixed systems), end-effector designs, sensor types, learning architectures, validation environments, and reported performance metrics. Results showed that harvesting and manipulation dominated the literature, followed by weeding, phenotyping, and counting. RGB-D cameras and YOLO-based detection models were the most prevalent, whereas LiDAR and multispectral sensors were increasingly used for navigation and diagnostics. Most systems remained at intermediate TRL stages (3-6), reflecting limited readiness for real-world deployment. This review concludes that advancing agricultural robotics requires standardized evaluation protocols, multi-season public datasets, and collaborative efforts to accelerate prototypes into large-scale implementation.

1. Introduction

Precision agriculture seeks to enhance productivity and sustainability by making site-specific decisions based on reliable data. In this context, the integration of robotics and computer vision represents a key technological driver for automating tasks that demand robust perception, reliable planning, and precise actuation in unstructured environments. Recent literature reports advances in harvesting using manipulators supported by multimodal perception and deep learning, as well as detection and counting for agronomic decision-making, and vision pipelines capable of operating with limited data. Additionally, improvements have been made in cluster localization and cutting-point identification under occlusions and variable lighting conditions [1]-[7].

Despite this progress, persistent research challenges remain: robustness under changing outdoor conditions, cross-domain generalization across various varieties, phenological stages, and devices, the heterogeneity of evaluation protocols hindering fair comparisons, the scarcity of reproducible resources such as code and datasets, and the consistent estimation of technology readiness levels (TRL) to guide field deployment. These challenges are evident in critical tasks such as harvesting, where perception-control coordination determines success rates; in weeding, which requires selectivity while maintaining effective coverage; and in navigation, which demands robust perception for stable guidance through dense vegetation and complex agricultural backgrounds [8]-[13].

To address these issues, one- and two-stage detectors optimized for real-time inference have been combined with multimodal sensing (RGB/RGB-D, thermal, LiDAR, multispectral/hyperspectral), pose estimation, and grasp planning, as well as precision spraying and laser weeding. Ground platforms integrate machine vision with localization and guidance (including ultra-wideband [UWB] tracking and row detection), while aerial systems employ multispectral and hyperspectral imaging for phenotyping and diagnostics. Evaluated as integrated perception-decision-actuation systems, these approaches have demonstrated improvements in accuracy, coverage, and operational stability in both field and greenhouse conditions [10]-[13].

The state of the art is organized along three axes: robotic platforms (manipulators, unmanned ground vehicles [UGV], and unmanned aerial vehicles [UAV]); sensing modalities (RGB/RGB-D, thermal, LiDAR, multispectral/hyperspectral, GPS-RTK, UWB); and artificial intelligence (AI) algorithms, including YOLO detectors, U-Net and Mask R-CNN segmenters, Transformer architectures, simultaneous localization and mapping (SLAM), and reinforcement learning (RL). Advances in object detection, plant segmentation, navigation line identification, and the estimation of crop structural or stress traits are evident; however, the diversity of datasets and performance indicators continues to hinder benchmarking and reproducibility across studies [3], [14], [15]. In this context, previous reviews have provided valuable insights into specific aspects of agricultural robotics but have not systematically addressed the integration of tasks, platforms, sensing modalities, and AI methods while also analyzing TRL distributions. Furthermore, the period 2021-2025 is particularly relevant given the rapid adoption of deep learning architectures such as YOLOv5-v8, Transformers, and reinforcement learning in agricultural robotics, which justifies the temporal scope of this review.

The research contribution is threefold: it presents a structured taxonomy that links robotic platforms, agricultural tasks, sensing modalities, and AI models; it proposes a conceptual framework illustrating the flow of information from perception to decision-making and actuation; and it provides a critical synthesis of performance metrics and TRL distributions to guide research priorities and accelerate the transition from prototypes to large-scale agricultural deployment.

2. Method

A systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to examine the integration of robotics and computer vision in precision agriculture. A search of specialized academic databases initially yielded 440 records, which, after a deduplication process, were reduced to 226 unique articles. Titles, abstracts, and full texts were screened according to predefined inclusion and exclusion criteria, resulting in a final corpus of 118 peer-reviewed journal articles. The review protocol was not formally registered (e.g., PROSPERO); however, adherence to PRISMA 2020 ensured transparency, and bias mitigation was addressed through double screening by independent reviewers with inter-rater agreement.

The selection process was structured into four PRISMA phases: identification, screening, eligibility, and inclusion to ensure transparency and reproducibility. Fig. 1 summarizes this workflow through a PRISMA diagram.

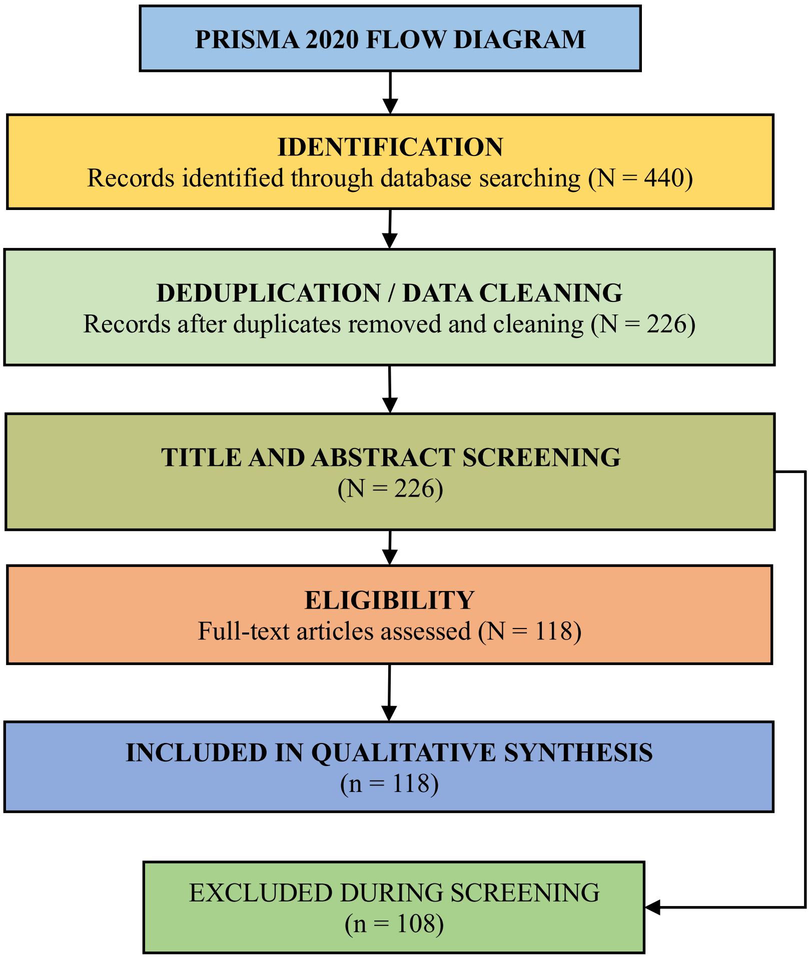

Fig. 1. PRISMA diagram of the study

2.1. Information Sources and Search Strategy

Searches were performed in major scientific databases indexed in engineering, computer science, and agricultural domains, including Scopus, Web of Science, IEEE Xplore, SpringerLink, and MDPI. Boolean queries were formulated in English, combining domain-specific terms (e.g., precision agriculture, smart farming), robotic platforms (unmanned aerial vehicles [UAV], unmanned ground vehicles [UGV], tractors, manipulators), and sensing or AI components (RGB, RGB-D, LiDAR, multispectral, hyperspectral, thermal, detection, segmentation, SLAM, control). The review covered publications from 2021 to 2025. This time window was selected because it captures the most recent adoption of deep learning architectures (YOLOv5-v8, Transformers, reinforcement learning) in agricultural robotics, representing a distinct stage of technological development. No language restrictions were applied, and only peer-reviewed journal articles were included.

2.2. Eligibility and Selection Process

Studies and articles were included if they described an operational robotic platform, UAV, UGV, tractor, manipulator, or fixed system integrated with vision or sensing technologies, such as RGB/RGB-D cameras, thermal sensors, LiDAR, multispectral or hyperspectral imaging, GPS-RTK, or UWB positioning. Eligible works implemented explicit algorithms or models, including object detection, segmentation, SLAM, control, or reinforcement learning.

They reported quantitative performance metrics (e.g., mean Average Precision [mAP], F1-score, Intersection over Union [IoU], Root Mean Square Error [RMSE], Multiple Object Tracking Accuracy [MOTA], cycle time, coverage, harvest success rate, or resource savings). Experimental validation in field, greenhouse, or laboratory conditions was required. Excluded works included articles that focused exclusively on IoT or cybersecurity without robotic vision integration, studies based solely on remote sensing, non-peer-reviewed materials, and non-journal publications. Article selection was conducted independently by two reviewers, and disagreements were resolved by consensus to ensure reliability.

2.3. Variable Extraction and Analytical Framework

For each article, data were extracted regarding the robotic platform (UAV, UGV, manipulator, fixed system), target task (harvesting, weeding, phenotyping and counting, spraying, navigation, SLAM), crop type, and experimental environment (field, greenhouse, laboratory). Additional variables included sensing modalities (RGB, RGB-D, thermal, LiDAR, NIR, multispectral/hyperspectral, GPS-RTK, UWB/IMU), AI models (YOLO families, Mask R-CNN, U-Net, Transformers, SLAM algorithms, reinforcement learning), sensor fusion strategies (temporal or multimodal), performance metrics (component-level and system-level), open resources (datasets and code), validation scope (number of trials, plots, or operational hours), and technology readiness level (TRL 1-9). These variables were organized according to the conceptual pipeline shown in Fig. 2, which illustrates the stages of a robotic system, from sensing and perception through data fusion, decision-making, and actuation, and maps metrics to each stage.

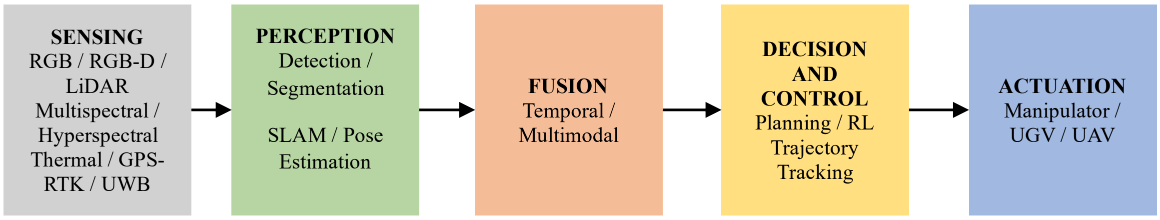

Fig. 2. Conceptual pipeline of agricultural robotic systems

2.4. Methodological Quality, Technology Readiness, and Bias Assessment

The quality of each study was assessed using a rubric (0-100) based on seven weighted criteria: relevance to robotics and vision (25), integration of robot, AI, and sensors (20), methodological quality (20), field validation (15), metrics and reporting clarity (10), reproducibility (5), and recency (5). In parallel, the technology readiness level (TRL 1-9) was estimated considering integration level, autonomy, robustness, and testing environment. Potential biases were analyzed, including scenario selection, sample size, absence of baselines, data leakage, image reuse, and lack of cross-validation. This structured assessment enabled consistent evaluation across studies and highlighted common methodological weaknesses, informing the interpretation of results.

3. Results

3.1. Thematic Classification of Articles

The reviewed literature was categorized into seven thematic groups, representing the main research directions in robotics and computer vision for precision agriculture. Each article was assigned to a single category based on its primary contribution, determined from the title, abstract, and methodology. This classification provides a structured overview of the current scientific landscape, highlighting the dominance of studies related to harvesting and the secondary, yet significant, focus on weeding and weed management.

As shown in Table 1, harvesting and manipulation represented the largest proportion (45 articles, 38.1%), confirming the centrality of automated fruit and vegetable collection in agricultural robotics research. Weeding and weed management accounted for 33 studies (27.9%), evidencing strong interest in selective elimination approaches. Phenotyping, counting, and monitoring appeared less frequently (14 articles, 11.9%), while spraying and precision applications were addressed in only 7 articles (5.9%).

Table 1. Thematic classification of the 118 reviewed articles according to their primary agricultural task

Category	Articles (n)	Ref.
Harvesting and manipulation	45	[1], [2], [4], [5], [6], [7], [10], [14], [15], [16], [17], [19], [21], [22], [23], [24], [25], [27], [29], [30], [31], [33], [35], [37], [39], [40], [41], [42], [43], [44], [46], [47], [48], [49], [50], [51], [52], [54], [56], [57], [58], [60], [61], [62], [63]
Weeding and weed management	33	[8], [9], [11], [12], [13], [18], [26], [28], [32], [34], [36], [38], [45], [53], [55], [59], [64], [65], [66], [67], [68], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81]
Spraying and precision applications	7	[82], [83], [84], [85], [86], [87], [88]
Phenotyping, counting, and monitoring	14	[3], [20], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100]
Autonomous navigation and SLAM	9	[101], [102], [103], [104], [105], [106], [107], [108], [109]
Multi-task systems and integration	3	[110], [111], [112]
Other (conceptual/simulation/hardware)	7	[113], [114], [115], [116], [117], [118]

3.2. Distribution of Platforms by Agricultural Task

The analysis of the 118 reviewed articles revealed a heterogeneous distribution of robotic platforms across agricultural functions. Table 2 presents the cross-tabulation of platform types (unmanned aerial vehicles [UAVs], unmanned ground vehicles [UGVs]/tractors, manipulators, and fixed systems) and the seven thematic categories. Fig. 3 provides a visual summary of this distribution.

Table 2. Distribution of robotic platforms classified by their primary agricultural task

Task / Platform	UAV (Aerial)	UGV/Tractor (Ground)	Manipulator	Fixed System	Total
Harvesting and manipulation	0	4	25	16	45
Weeding and weed management	6	24	1	2	33
Spraying and precision applications	1	4	1	1	7
Phenotyping, counting, and monitoring	5	1	1	7	14
Autonomous navigation and SLAM	0	3	0	6	9
Multi-task systems and integration	0	0	2	1	3
Other (conceptual/simulation/hardware)	1	1	1	4	7
Total	**13**	**37**	**31**	**37**	**118**

In harvesting and manipulation, manipulators represented the largest group, with 25 out of 45 studies (approximately 56%), reflecting the research emphasis on end-effectors and perception-control coordination for delicate crops. In weeding and weed management, ground-based platforms dominated, accounting for 24 out of 33 articles (approximately 73%), showing their suitability for large-scale field operations. Ground vehicles were also the leading platform in spraying and precision applications (4 out of 7). In phenotyping, counting, and monitoring, fixed systems were most frequently used, representing 7 out of 14 studies (approximately 50%), while UAVs were the second most frequent platform (5 out of 14). In autonomous navigation and SLAM, fixed sensing infrastructures were predominant (6 out of 9), complemented by UGV-based solutions. These distributions highlight how platform choice is closely aligned with task requirements, ranging from manipulators in harvesting to fixed sensing for monitoring.

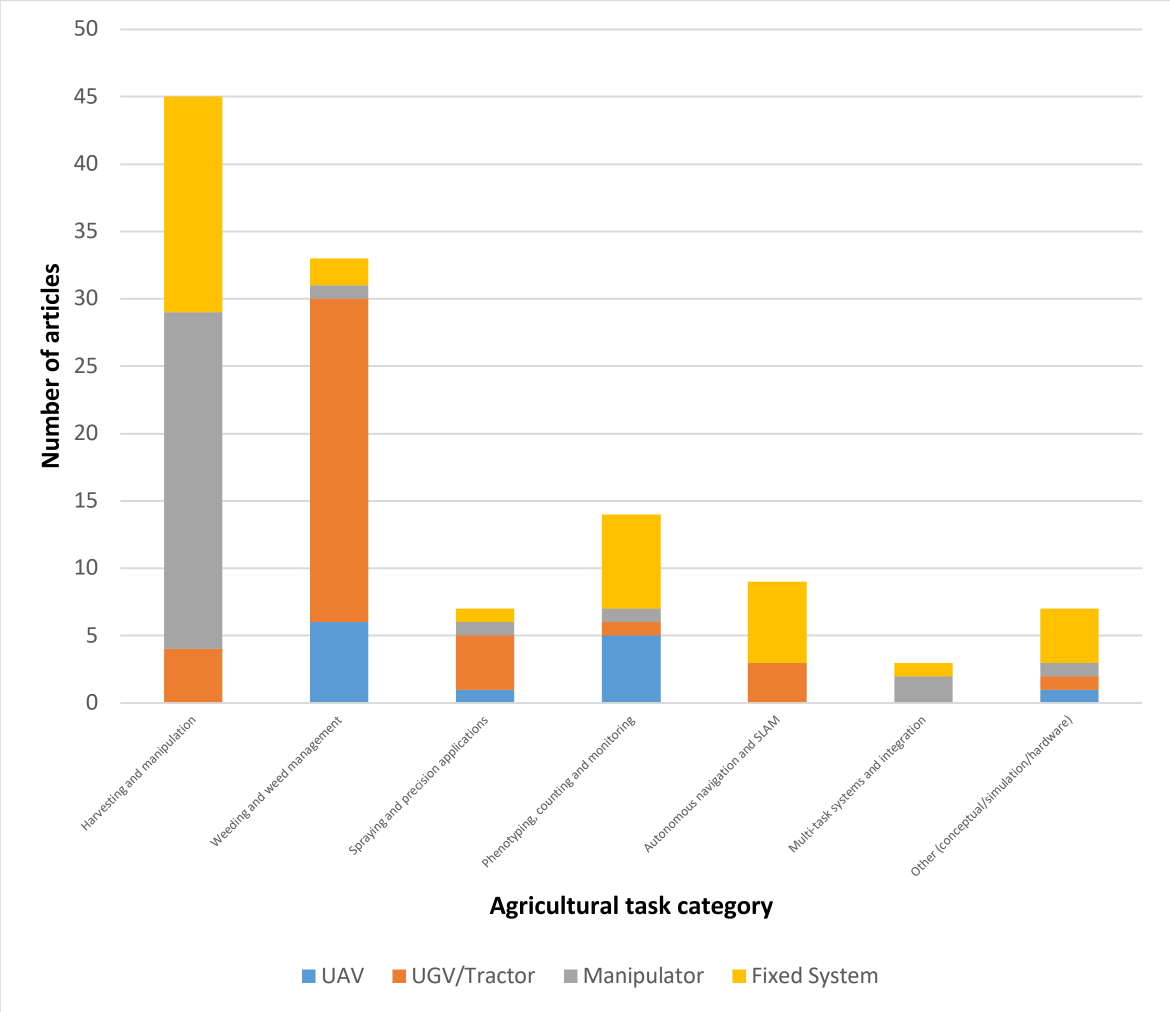

Fig. 3. Distribution of robotic platforms by main category of agricultural task

3.3. Prevalence of Sensors and AI Models

The analysis of the 118 reviewed articles revealed a diverse and complementary use of sensing technologies and AI models in agricultural robotics. The detailed distribution of sensing technologies is presented in Table 3, while the usage of AI models is summarized in Table 4. RGB and RGB-D cameras were the most widely used sensors, appearing in 92 articles (77.9%), confirming their role as the default option for detection, segmentation, and navigation tasks. LiDAR sensors were implemented in 22 articles (18.6%), primarily for three-dimensional mapping and navigation. Multispectral and hyperspectral sensors were reported in 20 studies (16.9%), mainly for phenotyping and stress diagnostics, while thermal/infrared imaging appeared in 12 articles (10.2%). GNSS RTK and UWB localization technologies were adopted in 16 studies (13.6%). The frequent use of multimodal sensor fusion highlights a clear tendency toward hybrid systems designed to enhance robustness under complex field conditions.

In terms of AI models, YOLO-based detectors (v3-v8) were reported in 36 studies (30.5%), indicating their predominance for real-time inference under occlusions. Mask/Faster R-CNN appeared in 32 studies (27.1%), remaining a strong benchmark for precision tasks. U-Net and its variants (15 studies, 12.7%) were mainly applied to semantic segmentation, while Transformer-based models (12 articles, 10.2%) showed steady growth. SLAM and VIO algorithms were integrated in 10 studies (8.5%), and reinforcement learning appeared in 6 studies (5.1%). The distribution of AI models demonstrates a balance between established architectures and the gradual adoption of emerging approaches such as Transformers and reinforcement learning.

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Table 3. Sensors

Technology	Articles (n)	Percentage (%)	Ref.
RGB/RGB-D cameras	92	77.9	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92]
LiDAR	22	18.6	[6], [19], [31], [43], [52], [59], [60], [63], [68], [70], [74], [77], [79], [81], [83], [87], [90], [92], [95], [97], [100], [103]
Multispectral/Hyperspectral	20	16.9	[12], [18], [28], [30], [33], [36], [41], [44], [48], [54], [58], [61], [65], [69], [73], [75], [80], [84], [89], [94]
Thermal/Infrared	12	10.2	[9], [21], [29], [35], [37], [42], [47], [50], [55], [62], [66], [72]
GNSS RTK / UWB localization	16	13.6	[31], [40], [43], [46], [51], [57], [60], [63], [70], [74], [77], [79], [81], [83], [87], [90]

Note: The sum of articles (n) exceeds the total of 118 because several studies employ multiple sensors simultaneously.

Table 4. AI Models

Technology	Articles (n)	Percentage (%)	Ref.
YOLO (v3-v8)	36	30.5	[3], [5], [7], [10], [13], [16], [18], [22], [25], [27], [30], [33], [36], [39], [42], [45], [48], [51], [54], [57], [60], [63], [66], [69], [72], [75], [78], [81], [84], [87], [90], [93], [96], [99], [102], [105]
Mask/Faster R-CNN	32	27.1	[4], [6], [8], [11], [14], [17], [20], [23], [26], [29], [32], [35], [38], [41], [44], [47], [50], [53], [56], [59], [62], [65], [68], [71], [74], [77], [80], [83], [86], [89], [92], [95]
U-Net / variants	15	12.7	[2], [9], [15], [19], [21], [24], [28], [31], [34], [37], [40], [43], [46], [49], [52]
Transformers (ViT, DETR)	12	10.2	[12], [18], [22], [27], [33], [39], [45], [51], [57], [63], [69], [75]
SLAM / VIO	10	8.5	[31], [40], [43], [46], [51], [57], [60], [63], [70], [74]
Reinforcement Learning (RL)	6	5.1	[45], [66], [88], [101], [110]

Note: Percentages were calculated over the total of 118 articles. The sum does not reach 100% because some studies employ diverse or hybrid AI models not included in the main categories.

3.4. Performance Metrics and Evaluation Standardization

The analysis of performance metrics reported in the 118 reviewed articles highlights the absence of unified evaluation standards for agricultural robotic systems, reflecting diverse application requirements and experimental conditions. Metrics varied widely in definition, units, sample sizes, and testing setups, particularly between field and greenhouse environments. Table 5 summarizes the most frequent evaluation metrics by task category, while Fig. 4 illustrates the distribution of IoU values across tasks, offering insight into performance variability.

For harvesting and manipulation, the primary indicators were fruit-level success rate, cycle time per fruit, and localization accuracy (IoU, RMSE). Reported mean cycle times ranged from approximately 5 to 20 seconds per fruit, influenced by crop complexity, occlusion levels, and manipulator design. Weeding and spraying systems were evaluated based on coverage, false positive/negative detection rates, and chemical reduction efficiency, with coverage frequently exceeding 90% in structured environments. In spraying and precision applications, drift and dosage uniformity were crucial, with drift typically below 10%.

Phenotyping and counting studies commonly reported mean absolute error (MAE) for counting tasks and IoU for segmentation-based trait analysis, with IoU values often exceeding 0.85. As shown in Fig. 4, phenotyping and navigation tasks achieved the highest IoU medians (≥0.90), whereas multi-task systems exhibited greater variability, consistent with their more complex integration challenges. Autonomous navigation prioritized path deviation (<5 cm), robustness (MOTA >0.9), and responsiveness (FPS). Multi-task platforms combined multiple metrics, underscoring the lack of unified frameworks.

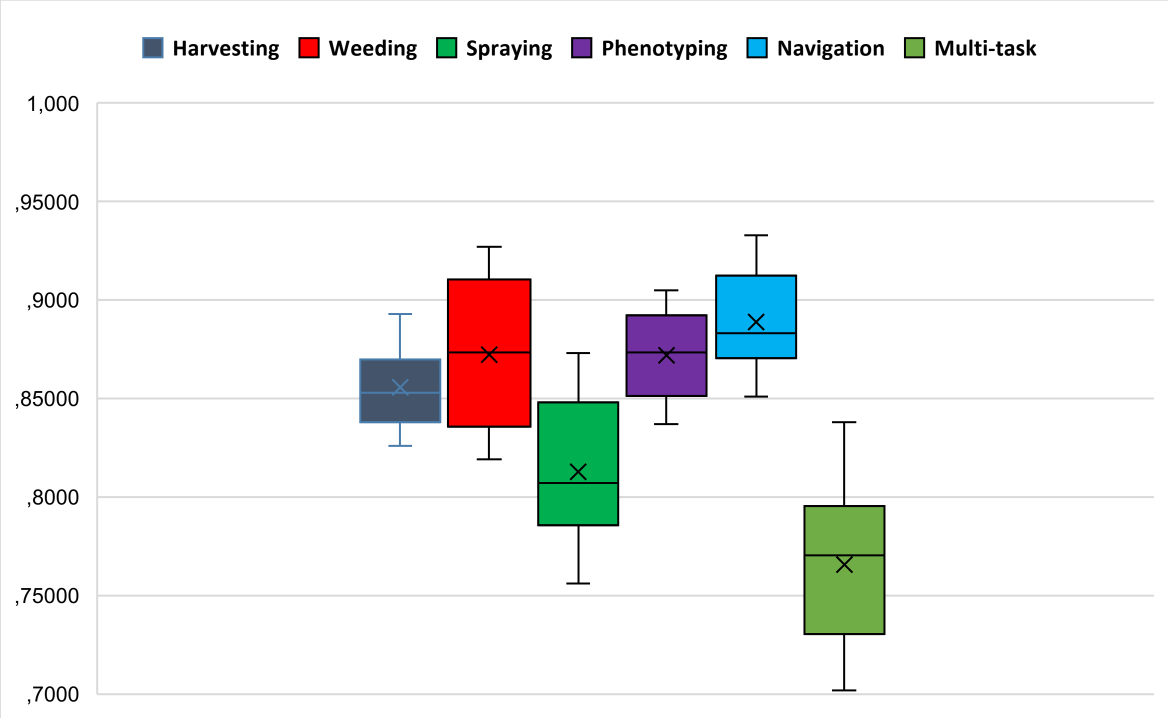

Fig. 4. IoU distribution by agricultural task

Table 5. Predominant performance metrics in agricultural robotics by task category

Task category	Key metrics	Reported trends
Harvesting and manipulation	Success rate (%), Cycle time (s), IoU, RMSE, Grasp/Pose accuracy	IoU: 0.82-0.91; Cycle time: 5-20 s/fruit
Weeding and weed management	Coverage (%), Precision/Recall, F1-score, False positive rate, Herbicide efficiency	F1: 0.84-0.93; Coverage: >90%
Spraying and precision applications	Coverage (%), Drift (%), Application uniformity, RMSE of dosage	Coverage: 85-95%; Drift: <10%
Phenotyping and counting	MAE, RMSE, IoU, Counting accuracy	MAE: 0.5-2.0 fruits/plant; IoU: >0.85
Autonomous navigation and SLAM	Path deviation (cm), MOTA, Failure rate, FPS	Path deviation: <5 cm; MOTA: >0.9
Multi-task systems and integration	Combined metrics (manipulation, navigation, vision)	Not standardized; tendency toward system-level metrics

3.5. Technology Readiness (TRL) and Biases in the Literature

The evaluation of TRL across the 118 reviewed articles was conducted in accordance with the NASA and European Commission TRL frameworks. Table 6 presents the distribution of studies across TRL levels. Most contributions were concentrated in TRL 3-4 (44.1%), representing proof-of-concept studies validated mainly in laboratories. A substantial proportion achieved TRL 5-6 (37.3%), reflecting pilot validation. Only 16 studies reached TRL 7-8 (13.5%), and 6 reached TRL 9 (5.1%). This distribution confirms that most agricultural robotics systems remain at an early-to-intermediate readiness level, with only a small fraction transitioning to advanced prototypes or commercial solutions.

Table 6. Distribution of articles by technology readiness level

TRL (Readiness Level)	Brief Description	Articles (n)	Percentage (%)
TRL 3-4	Proof of concept in laboratory settings	52	44.1
TRL 5-6	Validation in relevant environments (pilot)	44	37.3
TRL 7-8	Advanced prototypes tested in the field	16	13.5
TRL 9	Commercial product / full implementation	6	5.1
Total		**118**	**100.0**

By task category, harvesting and manipulation systems were predominantly at TRL 3-4, while weeding and spraying advanced more rapidly to TRL 5-7. Phenotyping and navigation technologies remained at pilot levels. These results suggest that task complexity and market incentives have a significant impact on readiness progression. The analysis of literature quality revealed several limitations: many studies relied on laboratory or greenhouse testing, dataset bias was frequent, and sample sizes were often small. Repeated use of the same datasets without cross-validation increased the risk of overfitting. These constraints limited scalability and underscore the importance of standardized evaluation protocols and publicly available datasets.

4. Discussion

4.1. Main Findings

The systematic review of the 118 included articles confirmed a clear trend of growth in robotics and computer vision for precision agriculture, with research strongly focused on automating critical agricultural operations. Harvesting and manipulation were the most studied categories, representing approximately 38% of the literature, reflecting their technical complexity and relevance for high-value crops [5], [23], [46], [71]. Studies on weeding and weed management followed closely (approximately 28%) [9], [11], [32], [54], while phenotyping, counting, and monitoring accounted for approximately 12%, supporting data-driven agronomic decision-making [58], [69], [94].

In sensing technologies, RGB/RGB-D cameras dominated (reported in 77.9% of works), while LiDAR (18.6%) and multispectral/hyperspectral sensors (16.9%) provided key capabilities for 3D reconstruction, navigation, and physiological crop analysis [54], [73], [80]. Among AI models, YOLO (v3-v8) and Mask/Faster R-CNN were the most widely used (30.5% and 27.1%, respectively) [13], [45], [63]. Transformer-based models and reinforcement learning (RL) showed growing use for contextual perception and adaptive decision-making [75], [93], [101]. TRL analysis revealed that over 80% of systems were positioned between TRL 3 and 6, spanning proof of concept to pilot validation [60], [79], [83]. These findings confirm the technical maturity gap, highlighting that most systems remain at the prototype level with limited transfer to real-world agricultural environments.

4.2. Comparison with Previous Studies

These findings are aligned with earlier reviews, which also identified harvesting as the most extensively studied domain in agricultural robotics [54], [80], [85]. This review, however, offers an updated and more comprehensive perspective, encompassing a broader range of crops, environments, platforms, and AI approaches published between 2021 and 2025. Notably, there is a marked increase in the adoption of SLAM/VIO techniques for navigation [60], [74], [83] and the design of multi-task systems integrating perception, actuation, and control [58], [90], [96]. Unlike earlier reviews that focused on isolated system components (e.g., perception or manipulation subsystems), this study introduces an end-to-end engineering perspective, combining task classification, TRL evaluation, performance metrics, and bias analysis. This broader integration enables the identification of systemic bottlenecks, such as the lack of reproducibility practices and the scarcity of field-validated datasets, which were not previously explicitly emphasized.

4.3. Implications and Interpretation of Findings

The findings reveal a clear evolution toward intelligent, multimodal robotic platforms. The strong prevalence of RGB/RGB-D cameras is due to their affordability and ease of integration, though they remain sensitive to environmental variations such as lighting and occlusion [30], [34], [52]. The incorporation of LiDAR and spectral imaging enables improved 3D mapping, crop structure modeling, and physiological assessments [54], [73], [80]. In AI, YOLO and R-CNN models remain dominant due to their balanced performance and computational efficiency. In contrast, Transformers and RL approaches demonstrate potential for better contextual perception, autonomy, and adaptability [75], [93], [101].

Metric standardization remains a key challenge. IoU, RMSE, and MOTA are commonly reported in phenotyping and navigation studies, but multi-task systems lack unified criteria [58], [90], [96]. Furthermore, the scarcity of public datasets, standardized benchmarks, and system-level evaluation metrics (such as end-to-end productivity, energy efficiency, or operational success rates) restricts reproducibility and cross-study comparability [60], [74], [83]. The limited statistical robustness of many studies, often relying on small sample sizes or short-term experiments, further constrains the generalizability of reported results. Expanding validation to multi-season, multi-location trials is crucial for bridging the gap between laboratory prototypes and commercial deployment.

4.4. Strengths and Limitations

The strengths of this review include its comprehensive scope, encompassing 118 articles, a structured analysis across five dimensions (task, platform, sensor, AI model, and TRL), and complete reference tables, which enhance reproducibility and transparency [63], [79], [84]. The strict adherence to PRISMA methodology and explicit bias evaluation further reinforces the validity of conclusions. In addition, the inclusion of TRL synthesis and bias analysis provides a novel perspective that extends beyond descriptive reviews, offering actionable insights for engineering-oriented research.

Nevertheless, several limitations must be acknowledged. Initial classification based on titles and abstracts may introduce selection bias [58], [90]. Variability in terminology and language could have limited the retrieval of relevant works, and the low representation of TRL 9 systems limits insight into commercial readiness [60], [74]. The concentration of research in highly mechanized agricultural regions reduces transferability to other production contexts. Moreover, few studies reported reproducibility practices such as code sharing, ablation studies, or cross-validation, which weakens confidence in performance claims. The lack of standardized protocols and publicly available datasets continues to hinder fair benchmarking and delays progress toward the development of reliable, field-ready agricultural robots.

5. Conclusion

This systematic review of 118 peer-reviewed articles (2021-2025) confirms that agricultural robotics research is advancing rapidly, with harvesting and weeding emerging as the most frequently addressed tasks. RGB and RGB-D cameras remain the predominant perception tools due to their affordability and ease of integration. At the same time, LiDAR and multispectral or hyperspectral sensors increasingly support 3D reconstruction, navigation, and physiological crop assessment. Algorithmically, YOLO and R-CNN families dominate, whereas transformer-based models and reinforcement learning are gaining visibility as promising approaches for contextual perception and adaptive decision-making. Despite these advances, most systems remain concentrated between TRL 3 and 6, underscoring the persistent gap between laboratory prototypes and commercially deployable solutions.

The main contribution of this review lies in the integration of task, platform, sensor, AI model, and TRL analyses into a unified engineering-oriented framework. By complementing this classification with the synthesis of performance metrics and bias assessment, the review offers a comprehensive and critical perspective that distinguishes it from earlier surveys. This approach enables the identification of systemic bottlenecks, such as the lack of reproducibility practices, limited dataset availability, and the absence of standardized evaluation protocols, which currently hinder progress.

Nevertheless, some limitations must be acknowledged. The focus on journal articles may have excluded relevant conference proceedings or industrial contributions. The restriction to the 2021-2025 period may have excluded seminal earlier studies, and variability in terminology across articles could have reduced the completeness of retrieval. These constraints should be taken into account when interpreting the findings and their broader implications.

Future progress in agricultural robotics will depend on the establishment of standardized task-specific protocols, the development of publicly available multi-season and multi-location datasets with agronomic metadata, and the implementation of validation practices that report costs, reliability, and reproducibility. Stronger collaboration between academia, industry, and farming stakeholders will be essential to accelerate technology transfer and ensure scalability. If these priorities are addressed, agricultural robotics can evolve from isolated prototypes into robust, deployable systems that contribute directly to sustainable, efficient, and resilient food production worldwide.

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