

Review

Robotic Arm Systems and Vision Technologies Across the Raspberry Production Cycle: A Review

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Abstract

Raspberry production remains highly labour-intensive, while most agricultural robotic systems are designed for individual operations, limiting their utilisation across the production season. This review evaluates robotic arm systems and associated vision technologies relevant to operations across the raspberry production cycle, with particular attention to their potential integration into multifunctional robotic platforms. Published studies were reviewed across six thematic areas: cane management, crop monitoring and yield estimation, targeted spraying, harvesting, end-effector solutions, and multifunctional, modular, and reconfigurable robotic platforms. Particular emphasis was placed on robotic system architecture, computer vision and sensing, target detection and localisation, manipulation, control, end-effector design, and reported operational performance. The reviewed literature shows that the greatest progress in raspberry-specific applications has been achieved in fruit detection, maturity assessment, crop monitoring, and harvesting, whereas integrated robotic solutions for pruning and targeted spraying remain limited. Within the reviewed literature, no raspberry-specific robotic arm platform that had been demonstrated across multiple operations of the production cycle was identified. However, the reviewed studies indicate that combining a common mobile platform and robotic arm with adaptable vision systems, control strategies, and interchangeable end-effectors could support broader seasonal use. Future research could therefore focus on integrating these components and validating multifunctional robotic systems under realistic raspberry production conditions.

Keywords: raspberry production; agricultural robotics; robotic arm; multifunctional robotic system; computer vision; precision agriculture



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1. Introduction

Raspberry production is an economically important horticultural sector worldwide, but it remains highly labour-intensive due to the extensive manual labour required throughout the growing season [1,2]. As the availability of agricultural labour continues to decline, automation technologies are increasingly being developed to improve the sustainability and economic viability of raspberry production [3–5].

Recent advances in agricultural robotics have accelerated the development of autonomous systems for horticultural applications [6–9]. Progress in autonomous agricultural robotics has also been driven by advances in sensing, computer vision, target localisation, and control, which provide the technological foundation for complete robotic systems [10–12]. To date, research has predominantly focused on robots designed for

individual agricultural tasks, particularly harvesting. However, harvesting represents only a small fraction of the annual production cycle, resulting in limited utilisation of harvest-specific robotic platforms [13]. This has motivated the development of multifunctional robotic systems capable of performing multiple operations throughout the production season, with the potential to improve equipment utilisation and economic viability [13–15]. Such systems are particularly promising for raspberry production, where management operations occur across multiple phenological stages, allowing a single robotic platform to support different tasks throughout the production cycle. This approach may be particularly beneficial for small-scale agriculture, where flexible robotic platforms can better address diverse operational requirements [13,16,17]. As schematically illustrated in Figure 1, raspberry production involves a sequence of phenological stages accompanied by management operations that extend across different parts of the production cycle [18,19]. Canopy management, crop protection, and resource management overlap with vegetative and reproductive development, while fruit-related operations extend from flowering and fruit set through ripening and harvest [5]. Figure 1 represents a generalised production cycle; the timing, duration, and overlap of individual stages and operations may vary depending on cultivar type, particularly between floricane- and primocane-fruited raspberries, as well as climatic conditions and the production system used [19].

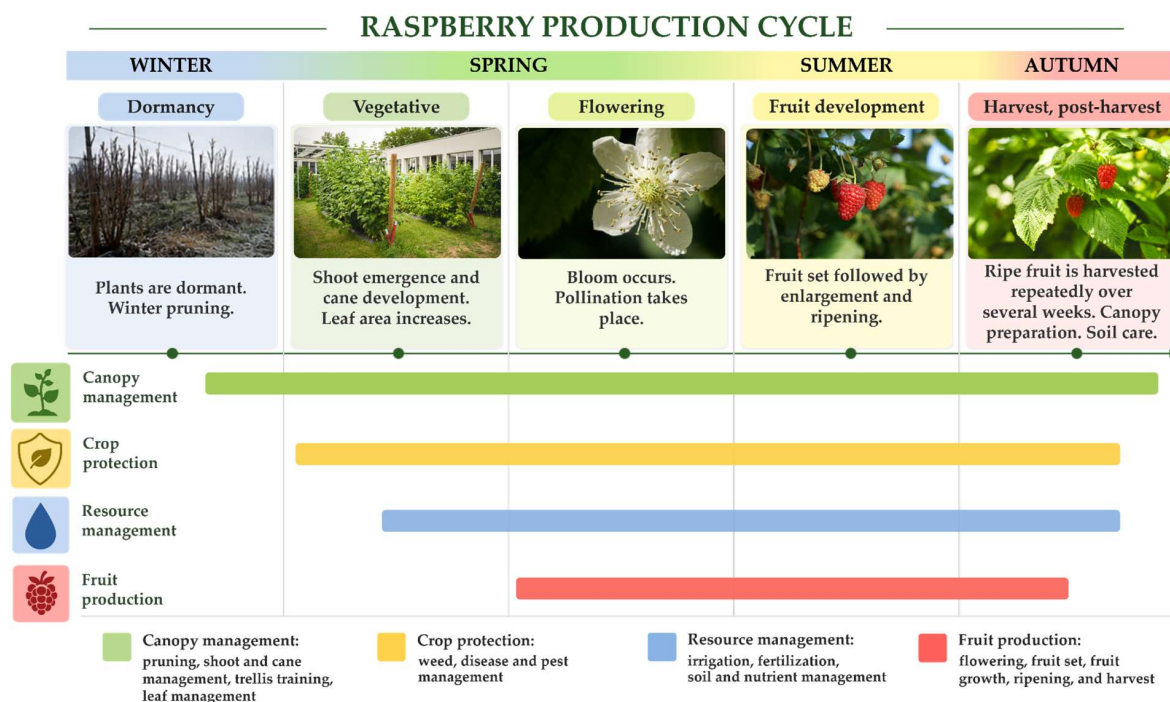


Figure 1. Seasonal raspberry production cycle, phenological stages, and associated crop management operations.

Developing such multifunctional systems is, however, technically demanding. Operations performed across the production cycle impose different requirements on perception, manipulation, tool positioning, and physical interaction with the crop, while the same robotic platform must remain functional under changing plant and environmental conditions [12,20,21]. Delicate fruits, such as raspberries, exhibit large variability in size, weight and shape, which complicates reliable robotic manipulation and increases the risk of damage during harvesting operations [22–25]. Another challenge arises from the rapid and non-uniform ripening of raspberries. Individual fruits within the same plant do not reach harvest maturity simultaneously, requiring repeated and selective harvesting [22]. Because ripeness also affects fruit detachment properties, robotic systems must accurately

distinguish harvestable fruits from unripe or overripe ones and adapt the applied forces accordingly. For example, in Junge et al. [23] detachment-force settings of 1.4, 2.0, and 2.8 N were used to represent the variability encountered among raspberries at different ripeness levels during the development of a robotic harvesting controller. Beyond fruit manipulation, robotic systems must also maintain reliable perception, localisation, and positioning under variable outdoor conditions and changes in canopy structure throughout the season [9,26]. These conditions can impair mobility and perception accuracy and may reduce the precision of target localisation, tool positioning, and manipulation. Reliable field operation therefore requires mechanically robust and environmentally protected robotic platforms, together with perception systems, robotic arms, and end-effectors capable of maintaining accurate performance under variable outdoor conditions [6,13,21].

Several approaches can be considered to increase the flexibility and utilisation of agricultural robotic systems. One possibility is the use of modular robotic arms. Zeis et al. [27] proposed a robotic arm composed of identical joint modules connected in series, allowing robotic arms with different kinematic configurations to be assembled by adding or removing individual modules. This approach enables the kinematic structure and workspace of the robotic arm to be adapted to specific task requirements. Another approach involves the use of multiple robotic arms operating in parallel, which can increase harvesting productivity and operational efficiency [22]. However, this configuration primarily improves task throughput rather than extending the range of operations that the platform can perform. A further and potentially more broadly applicable approach would be the development of a multifunctional mobile platform equipped with a single robotic arm and interchangeable end-effectors. Such a system could perform different operations throughout the annual production cycle using the same mobile platform and robotic arm [13,28]. This could increase annual equipment utilisation and distribute investment costs across multiple tasks, thereby potentially improving economic viability, particularly for small-scale farms [29].

The aim of this review is to identify and evaluate robotic arm systems and enabling vision technologies relevant to autonomous operations across the raspberry production cycle. The review examines robotic arm-based technologies relevant to cane management, crop monitoring and yield estimation, precision crop protection, and harvesting from a whole-season, system-level perspective. Where complete raspberry-specific solutions are not yet available, robotic arm systems and associated perception technologies developed for other horticultural crops are considered with respect to their potential transferability to raspberry production. The synthesis focuses on robotic arm and end-effector design, vision-based perception, and artificial intelligence and control methods, and is used to identify current technological limitations, research gaps, and future directions towards multifunctional robotic arm systems for raspberry production.

2. Materials and Methods

A literature search was conducted to identify studies relevant to robotic arm systems and associated vision technologies across the raspberry production cycle. The search primarily used the Web of Science Core Collection and Scopus databases and was organised into thematic areas corresponding to cane management, crop monitoring and yield estimation, targeted spraying, harvesting, end-effector technologies, and multifunctional robotic platforms. Because terminology differed substantially among these application areas, search terms were adapted to each topic rather than applying a single uniform search string. Raspberry-specific keywords, including “raspberry” and “*Rubus idaeus*”, were combined with operation- and technology-specific terms such as “robotic arm”, “robotic manipulator”, “computer vision”, “deep learning”, “RGB-D”, “pruning”, “yield estimation”, “targeted spraying”, “harvesting”, “end-effector”, “modular robot”, and “multifunctional robotic

platform”. Raspberry-specific studies were prioritised; where complete solutions were unavailable, studies from other horticultural crops were included when their robotic architecture, sensing, manipulation, end-effector design, or control principles were considered transferable to raspberry production. The primary search focused on studies published between 2016 and 2026, while earlier foundational publications were included where necessary to provide technological or agronomic context. Peer-reviewed journal articles and conference papers were prioritised, with selected theses, patents, technical reports, and commercial sources included only when relevant information was not available in the scientific literature.

Figure 2a shows the temporal distribution of the publications analysed in this review. The number of relevant studies remained relatively low until 2021, followed by a clear increase from 2022 onwards. The highest number of analysed publications was recorded in 2025, indicating a marked recent growth in research related to robotic and vision-based technologies relevant to raspberry production. The lower number of publications in 2026 should be interpreted with consideration of the incomplete publication year at the time of the literature search. Figure 2b presents the distribution of the analysed publications across the six thematic areas considered in this review. The categories correspond to: I, cane management; II, crop monitoring and yield estimation; III, targeted spraying and related precision applications; IV, harvesting; V, end-effector technologies; and VI, multi-functional, modular, and reconfigurable robotic platforms. For categories I and IV, the bars are subdivided according to the type of analysed study, with the blue segment representing computer vision focused studies and the grey segment representing robotic solutions. This subdivision reflects the structure of the cane management and harvesting sections, where perception-related studies and complete robotic systems are discussed separately. The distribution further indicates that the available literature is unevenly represented across the different stages of the raspberry production cycle.

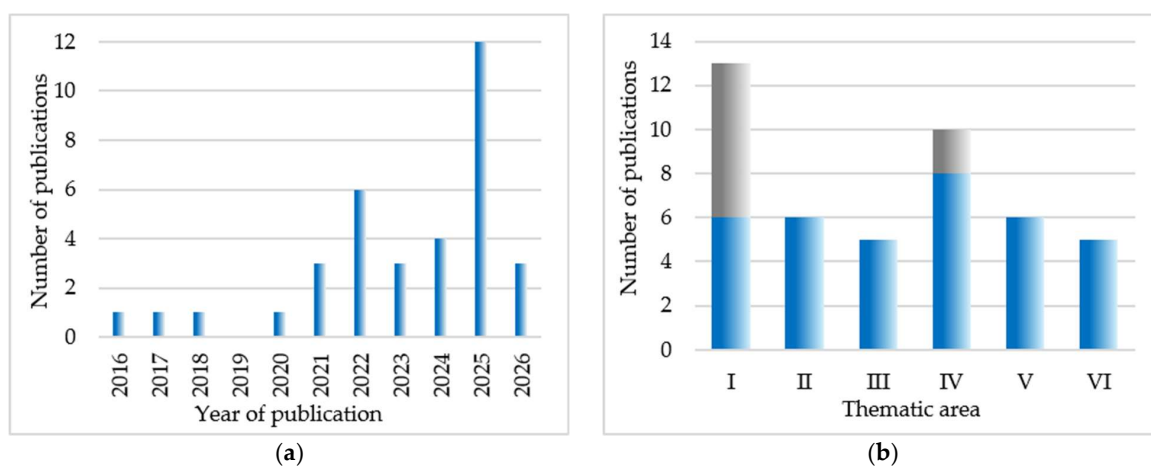


Figure 2. Distribution of the analysed publications: (a) by year of publication and (b) by thematic area.

The overall structure of the review is presented in Figure 3, including the main thematic areas addressed in the Results Section and their subsequent synthesis in the Discussion and Conclusions. In the Results Section, performance metrics were extracted as reported in the original studies. Because the reviewed studies differed in crop or cultivar, dataset composition, experimental environment, sensor configuration, level of autonomy, and definitions of successful operation, the reported metrics were not statistically normalised or pooled. They are therefore interpreted as study-specific performance indicators rather than directly comparable benchmarks.

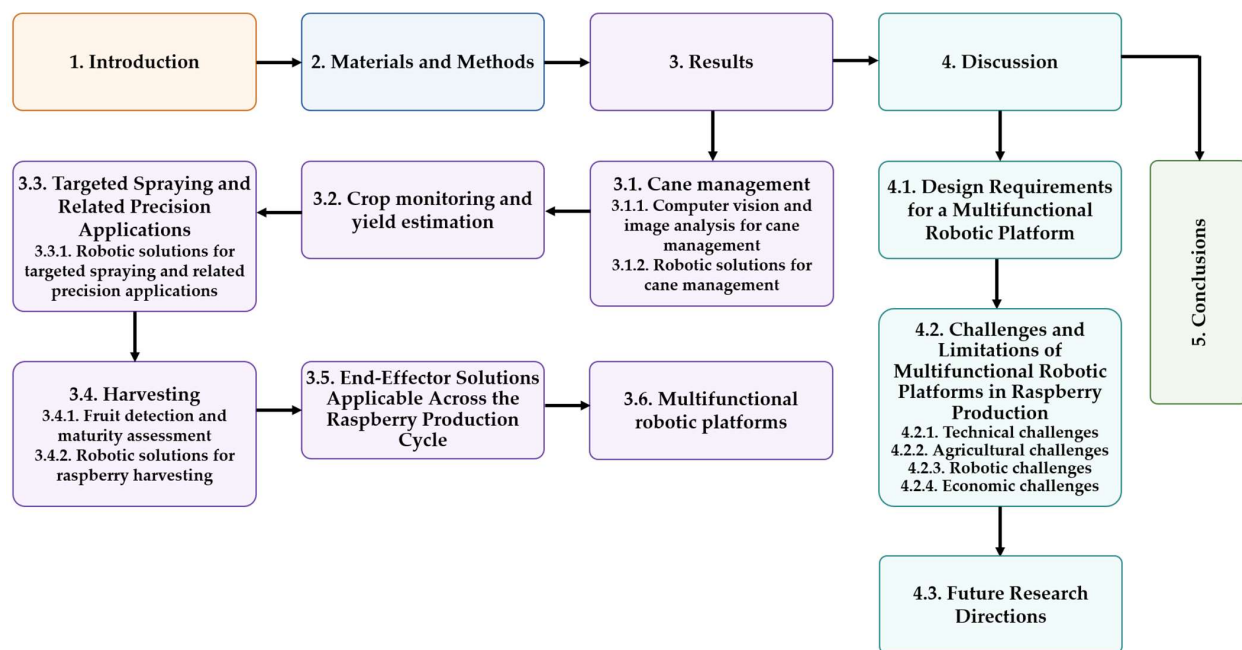


Figure 3. Schematic overview of the manuscript structure and thematic organisation of the reviewed robotic applications in raspberry production.

3. Results

3.1. Cane Management

Cane management not only comprises a range of important cultivation practices performed largely during dormancy but also at different stages of the growing season. These operations aim to maintain appropriate cane architecture, improve light penetration and air circulation within the canopy, and promote high fruit yield and quality [1]. These operations, including pruning, shoot thinning, and sucker removal, are traditionally labour-intensive and require repeated on-site interventions.

In raspberry production, pruning is considered an essential cultivation practice through which cane density is regulated, air circulation within the canopy is improved, harvesting operations are facilitated, and plant productivity is maintained. However, the automation of pruning is complicated by the dense and highly unstructured arrangement of raspberry canes. To perform this task autonomously, target canes must be accurately identified, collision-free trajectories must be generated, and damage to surrounding vegetation must be avoided. Furthermore, sufficient positioning and cutting accuracy must be achieved to ensure clean cuts that promote healthy regrowth. Although substantial advances have been made in perception technologies, the integration of sensing, motion planning, obstacle avoidance, and cutting mechanisms into a robust autonomous pruning system remains a significant research challenge [30]. Although robotic pruning has been extensively investigated for grapevines and, more recently, for planar fruit trees such as sweet cherry [31,32], no fully integrated robotic pruning system has yet been reported for raspberry production. Existing studies on raspberries primarily focus on harvesting, while pruning-related research is limited to perception algorithms such as cane segmentation or cutting-point detection.

3.1.1. Computer Vision and Image Analysis for Cane Management

In robotic cane management, computer vision and image analysis are used to detect, classify, and localise relevant plant structures and target points prior to physical manipulation [30,33,34]. As studies specifically addressing raspberry cane management remain

limited, relevant approaches developed for other horticultural fruit crops have also been considered. Selected studies, together with the sensing and computer vision methods employed and their reported performance, are summarised in Table 1.

Table 1. Overview of computer vision methods and reported performance for cane management in raspberry and other delicate fruit crops.

Source	Operation	Model/Input	mAP@0.5 [%]	Precision [%]	Recall [%]	F1-Score [%]	Accuracy [%]
Kaplan et al. [35]	Florican shrub detection from UAV imagery	YOLOv8s, YOLO11s, YOLO12s; RGB and multispectral UAV imagery	99.5	98.8–99.9	99.4–99.9	99.5–99.9	–
Khanal et al. [5]	Primocane/florican classification for selective pruning	Linear SVM; VIS–NIR–SWIR spectroscopy	–	–	–	–	91.6–100.0
Bhusal et al. [36]	Primocane detection and 3D localisation	SegNet + stereo vision	–	–	–	–	>87
Pomykala et al. [37]	Truss and runner identification for pruning	ResNet50, ResNet101; semantic segmentation	–	Trusses: 91; Runners: 3	Trusses: 95; Runners: 1	Trusses: 92; Runners: 2	–
Ahmadi et al. [38]	Runner detection and localisation	ResNet50/101 segmentation + AutoML object detection; RGB	–	74–88	62–81	68–84	–
Zhou et al. [39]	Runner detection and segmentation	YOLOv8x-seg, YOLOv11x-seg; ground and UAV RGB imagery	84	85	76	80	–

Early approaches to computer vision-based cane management in raspberry production were presented by Khanal et al. [5] and Bhusal et al. [36], addressing complementary perception tasks required for automation. Khanal et al. investigated the differentiation of one-year-old primocanes and two-year-old floricanes as a prerequisite for selective pruning. Since both cane types exhibit similar colour, shape, and size during the dormant season, spectral reflectance characteristics associated primarily with chlorophyll and moisture content were analysed, and selected wavelengths were subsequently used for SVM-based classification. In parallel, Bhusal et al. developed a machine vision system for the detection and 3D localisation of raspberry canes under field conditions using SegNet-based semantic segmentation and stereo vision. The system was integrated with a previously developed mechanism for automated bundling and tying of primocanes, demonstrating the potential of combining visual perception with mechanized cane management operations.

Computer vision has also been investigated for broader monitoring of florican raspberry plantations. Kaplan et al. [35] applied YOLO-based object detection to identify florican raspberry shrubs from UAV-acquired imagery. The study considered both conventional RGB images and multispectral data, including near-infrared (NIR), red-edge (RE), red (R), and green (G) spectral bands, and evaluated the transferability of the detection models across different imaging modalities. Although individual canes were not distinguished and no specific cane-management operation was performed, the study demonstrates the application of computer vision for automated detection and monitoring of florican raspberry stands. This represents a broader perception approach that could support the future development of more detailed vision systems for cane-level monitoring and management.

Beyond raspberry-specific cane management, related computer vision approaches have been investigated in other delicate fruit crops, particularly strawberries, where runner management represents a comparable pruning task. Pomykala et al. [37] proposed semantic segmentation using ResNet50 and ResNet101 to distinguish strawberry runners and trusses

as a basis for future automated pruning. While high performance was achieved for truss detection, runner recognition remained challenging. Subsequently, Ahmadi et al. [38] introduced a two-step framework combining ResNet-based semantic segmentation with object detection to detect and localise individual runners. The approach substantially improved runner recognition, achieving an IoU of 72% and an F1-score of 84% for the best-performing cultivar. More recently, Zhou et al. [39] extended runner detection to more diverse field conditions by integrating ground-based and UAV imagery acquired at different altitudes. YOLOv8x-seg and YOLOv11x-seg were evaluated for both runner detection and segmentation, with models trained on combined ground and aerial datasets showing improved generalization across different resolutions and viewpoints. YOLOv11x-seg achieved F1-scores of 79–82% for runner detection across the three imaging platforms. The study further identified UAV imaging at 5 m above ground level as an effective compromise between detection performance and data acquisition efficiency, supporting scalable runner monitoring and future automated runner management.

Comparatively, the raspberry-specific studies address biologically relevant prerequisites for cane management, particularly cane-type discrimination and 3D localisation [5,36], whereas the strawberry runner studies mainly demonstrate transferable segmentation and detection strategies [37–39]. These approaches are therefore transferable primarily at the level of perception methodology, but not directly in terms of target definition or reported performance, because the studies address different crop structures, target objects, imaging conditions, and management objectives [5,36–39]. Likewise, the very high performance reported for UAV-based raspberry shrub detection [35] should not be interpreted as evidence of cane-level pruning readiness, because the study targeted whole shrubs rather than individual canes and did not perform a specific cane-management operation.

3.1.2. Robotic Solutions for Cane Management

Robotic cane management requires the integration of perception, robotic manipulation, motion planning, and control to identify relevant plant structures and perform targeted operations under variable field conditions [30,33]. As complete robotic-arm systems developed specifically for raspberry cane management remain limited, related robotic solutions have been investigated in other crops, particularly for pruning and other targeted plant-management operations. These systems provide relevant examples of sensing, manipulation, end-effector design, motion planning, and autonomous control that may be transferable to raspberry production. Their technical configurations are summarised in Table 2, while the reported operational performance is presented in Table 3. The studies summarised in Table 3 report different types of quantitative performance indicators because they address different crops, pruning operations, robotic architectures, and stages of system development. The overall task success and execution time are therefore reported in separate columns where available, while additional study-specific indicators, including cut-point accuracy, object-detection performance, branch-reaching success, trajectory error, pose-correction success, fruit damage, and workspace or motion-planning performance, are reported in the “Other performance metrics” column. These values provide a quantitative overview of the individual systems, but they should not be interpreted as directly comparable benchmarks because the studies differ in experimental conditions, target structures, evaluation procedures, and definitions of successful operation.

Table 2. Technical characteristics of robotic systems for cane management and related operations.

Source	Model	Vehicle	Robot	Communication	End-Effector	Sensors	Computing	Control	Autonomy
Silwal et al. [31]	Faster R-CNN-VGG16; SVD-SVM; ICP	Clearpath Warthog UGV (Clearpath Robotics, Kitchener, ON, Canada)	UR5 (Universal Robots A/S, Odense, Denmark) + 1.35 m linear axis; 7 DoF	ROS Kinetic; NTP	Bypass shears; 8 N·m servo	Dual active-light stereo; RTK-GPS; IMU; encoders	Xeon E5 (Intel Corporation, Santa Clara, CA, USA); 32 GB; GTX 1080 (NVIDIA Corporation, Santa Clara, CA, USA); Ubuntu 16.04	MoveIt; RRT-Connect; Cartesian planner; MPC; EKF	Fully autonomous
You et al. [32]	pix2pix; SegFlow2; Mask R-CNN; PPO	Utility vehicle	UR5e + 1 m linear axis; 7 DoF	ROS; serial links	Electric bypass shears; max. 32 mm	RealSense D435 (Intel Corporation, Santa Clara, CA, USA); wrist F/T sensor	ROS PC; XPS-15 (Dell Technologies Inc., Round Rock, TX, USA); GTX 1050 Ti	RRT-Connect; vision-force control	Semi-autonomous
Botterill et al. [40]	SVMs; stochastic image grammar; rule-based AI	Winch-pulled straddle platform	UR5; 6 DoF	ROS; rosbag	6 mm mill-end cutter; 100 W, 24,000 rpm motor	3 × 1.3 MP Grasshopper2 RGB cameras (Point Grey Research Inc., Richmond, BC, Canada)	6-core Intel i7 (Intel Corporation, Santa Clara, CA, USA), 2.93 GHz desktop PC	RRT-Connect; OMPL; collision avoidance; stop-and-cut control	Semi-autonomous
Hizatate et al. [41,42]	YOLOv11n-seg; YOLOv11n; FastDTW; MST	Autonomous golf-cart platform; rear-wheel drive	2 × FANUC CRX-10iA/L (FANUC Corporation, Oshino, Yamanashi, Japan); 6 DoF	CAN-BUS; serial communication	Modified electric pruning shears; 40 mm opening; Hall feedback	2 × DS77C Pro RGB-D (Vzense, Qingdao, Shandong, China); RealSense D405; RTK-GNSS; IMU; Hall sensor	Onboard computer	MoveIt; OMPL; trapezoidal path + RRT-Connect	Fully autonomous
Fujinaga [13]	YOLOv5; DL semantic segmentation + rule-based cut-point detection	CuGoV3 crawler (CuboRex Co., Ltd., Tokyo, Japan)	ViperX 300 (Trossen Robotics, Downers Grove, IL, USA); 6 DoF	ROS; Bluetooth; network/wired links	Interchangeable gripper/scissor cutting mechanism	RealSense D435i RGB-D	Intel Core i7; 32 GB RAM	ROS; state-based Search → Analysis → Harvest	Semi-autonomous

Table 2. Cont.

Source	Model	Vehicle	Robot	Communication	End-Effector	Sensors	Computing	Control	Autonomy
Zahid et al. [43]	DH-based kinematic simulation	Stationary frame	3P + 3R; 6 DoF	Serial	60 mm shear; ≤ 25 mm	Limit switches; Hall; no vision	Arduino Mega (Arduino S.r.l., Monza, Italy); MATLAB R2019b (The MathWorks, Inc., Natick, MA, USA)	Forward kinematics; GUI	Manual target input
Molaei & Ghatrehsamani [44]	Task-based kinematic optimization; NSGA-II	Mobile straddle platform proposed	Prubot; 7R; 7 DoF	N/R	44 cm shear-type pruner	N/R	i7-4500U; MATLAB; CoppeliaSim (Coppelia Robotics AG, Zurich, Switzerland)	Sampling-based planning + IK	Simulation only

Table 3. Reported performance of robotic systems for cane management and related operations.

Source	Crop	Operation	Success	Time	Additional Quantitative Performance Metrics
Silwal et al. [31]	Grapevine	Spur pruning	87%	213 s·vine ^{−1}	Cut-point accuracy = 94%; mAP = 0.93; segmentation F1 = 0.91
You et al. [32]	Sweet cherry	Dormant pruning	58%	35.1 s·cut ^{−1}	Branch-reaching success = 69%; scan time = 284 s
Botterill et al. [40]	Grapevine	Cane pruning	2/6 cuts completed	≈120 s·vine ^{−1}	All 6 targets reached; trajectory error <1%; 2D detection P/R = 58/49%
Hizatate et al. [41,42]	Grapevine	Spur pruning	69.7% single-pass; 83.1% two-stage; 82% with pose correction	11.2/10.2 s·shoot ^{−1} ; 122.9/183.5 s·vine ^{−1}	Pose-correction success = 90%; branch-mask P/R/mAP50 = 0.86/0.84/0.88; bud-detection P/R/mAP50 = 0.79/0.64/0.70
Fujinaga [13]	Tomato; Strawberry	Harvesting; adaptable to truss pruning	Strawberry: 80% harvest, ~53% operation success	Tomato: 34 ± 12 s·fruit ^{−1} ; Strawberry: 21 ± 6 s·operation ^{−1}	Strawberry damage = 25%; detection accuracy = 96.1–97.2%; module exchange ≈10 min
Zahid et al. [43]	Apple	Pruning	≈100/≈100 test cuts completed	0.75 s·cut ^{−1}	All selected targets reached; clean cuts up to 25 mm
Molaei & Ghatrehsamani [44]	Grapevine	Cane pruning	N/A	≤5 s Lazy RRT	11 simulated cut-points; workspace covered the full vine

Note: N/A denotes Not Applicable.

The reviewed pruning systems show a progression from proof-of-concept perception–cutting integration towards more complete autonomous platforms combining crop reconstruction, motion planning, navigation, and local sensing [31,32,40–42]. Botterill et al. [40] demonstrated an integrated perception–planning–cutting workflow for grapevine cane pruning (Figure 4b), although overall reliability was affected by errors accumulated across individual system components. Silwal et al. [31] extended this approach to a fully autonomous mobile platform with an enlarged robotic-arm workspace (Figure 4c), while You et al. [32] demonstrated the additional importance of force-aware interaction during selective tree pruning (Figure 4a). More recently, Hizatate et al. [41,42] addressed inaccuracies in plant-structure estimation through collision-aware planning, obstacle-model updates, and end-effector-based pose correction. Their robotic system is shown in Figure 4d. Reliable robotic pruning therefore requires accurate target detection together with effective coordination of perception, motion planning, manipulation, and cutting.

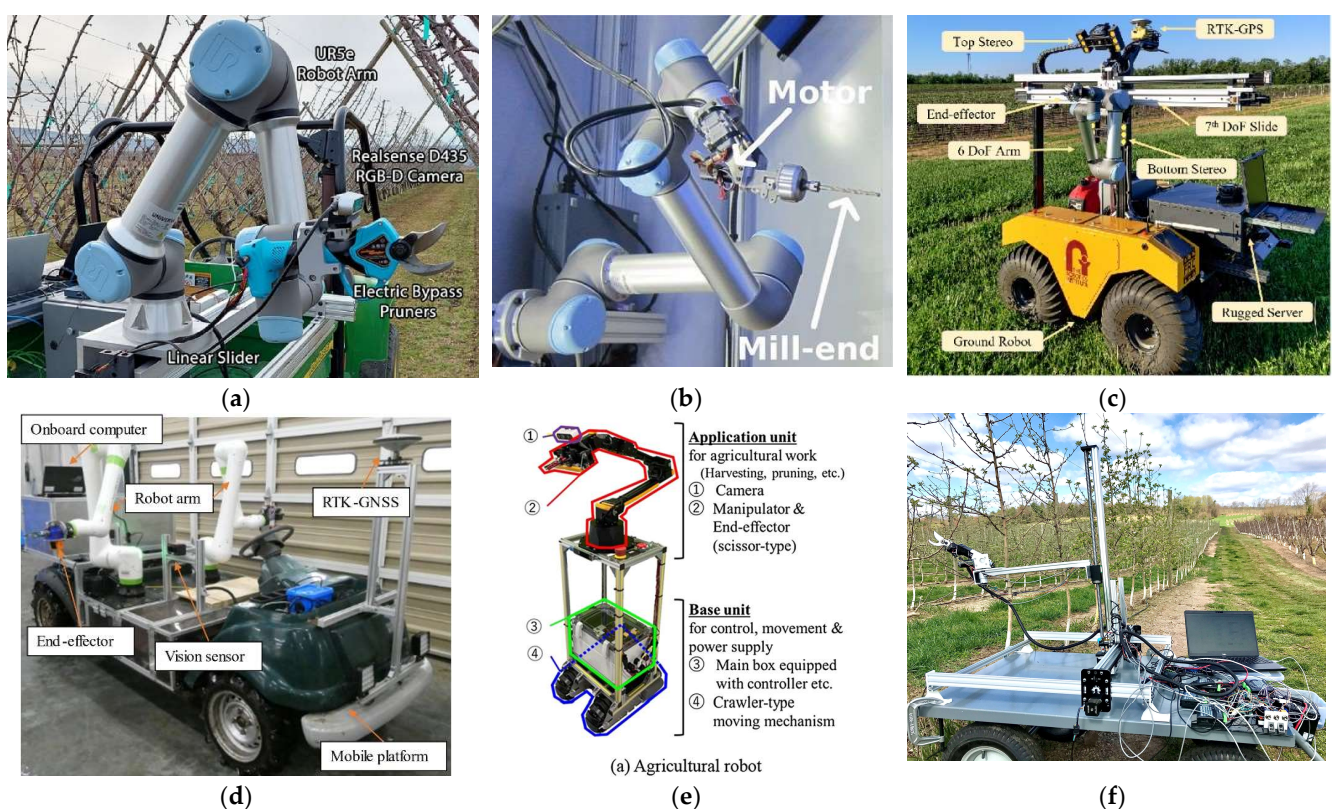


Figure 4. Integrated robotic systems for cane management and related pruning operations in horticultural crops: (a) You et al. [32]; (b) Botterill et al. [40]; (c) Silwal et al. [31]; (d) Hizatate et al. [41,42]; (e) Fujinaga [13,29]; and (f) Zahid et al. [43].

Complementary studies have focused more specifically on robotic arm and end-effector design. Zahid et al. [43] developed a 6 DoF pruning system combining a Cartesian positioning mechanism with a 3R pruning end-effector (Figure 4f), demonstrating the importance of cutter orientation and workspace accessibility in dense tree canopies. Field tests confirmed that branches up to approximately 25 mm in diameter could be cut over a wide range of orientations, although target positions were provided manually rather than through an integrated vision system. Molaei and Ghatrehsamani [44] approached the same problem from a kinematic-design perspective, using multi-objective optimisation to develop a 7 DoF grapevine pruning robotic arm and evaluating workspace coverage and motion-planning performance in simulation. These studies highlight robotic arm dexterity and

target accessibility as important design considerations even before autonomous perception and control are integrated.

A further approach is represented by modular robotic platforms that were not primarily developed for pruning but offer architectures potentially adaptable to cane-management operations. Fujinaga et al. [13,29] demonstrated a general-purpose platform (Figure 4e) in which the mobile base and core control infrastructure can support different application units, while the robotic-arm configuration allows task-specific mechanisms and perception functions to be adapted according to the operation. Although the platform was experimentally evaluated mainly for harvesting and monitoring, its modular design illustrates how pruning-related functions could potentially be incorporated into a multifunctional agricultural robot. The platform itself was explicitly designed around interchangeable application units and shared base infrastructure.

In addition to research reported in the scientific literature, relevant industrial developments can also be identified. A 2025 patent assigned to Kubota describes a fruit-tree pruning system that uses sensor-derived information to classify canes as retained or removed and to determine three-dimensional cutting points for robotic pruning [45]. While the patent does not report field-performance data, it indicates commercial interest in transferring perception-based pruning approaches from research to practical applications.

For transfer to raspberry production, the most relevant elements of these pruning systems are the enlarged robotic arm workspace [31], collision-aware motion planning, and local target-position correction [41,42]. Equally important is the integration of perception, motion planning, cutting tools, and autonomous control [31,32,40–42]. Their reported success rates and cycle times, however, cannot be directly extrapolated to raspberry production because the systems were evaluated in different crops, plant architectures, and experimental conditions [31,32,40–42]. Raspberry cane management additionally requires discrimination between biologically different cane types [5], reliable cane detection and 3D localisation [36], collision-free access within a dense and unstructured canopy, and accurate cutting without damaging surrounding vegetation [30]. Seasonal changes in plant structure and target visibility further increase the requirements on perception and manipulation. This combination of structural interpretation, target selection, collision avoidance, and accurate cutting helps explain why integrated robotic pruning remains less mature in raspberry production than harvesting.

3.2. Crop Monitoring and Yield Estimation

Crop monitoring and yield estimation are important aspects of raspberry production, as they provide information on crop development, plant condition and potential productivity during the growing season [18,46]. Reliable assessment of these parameters can support crop management and production planning [47,48]. Conventional approaches, however, often rely on manual observations and sampling, which can be labour-intensive and difficult to apply consistently on a larger scale [49].

The studies included in this section focus specifically on raspberry production. Recent work has explored the use of imaging, sensing, computer vision and machine learning for monitoring plant and fruit development, assessing crop condition and stress responses, estimating yield-related traits, and evaluating fruit health and quality. Table 4 summarises the main applications, sensing and analytical approaches, and reported performance of these raspberry-specific studies. The individual studies are discussed in more detail below.

Table 4. Overview of computer vision and spectral imaging approaches for raspberry crop monitoring, phenotyping, yield estimation, stress detection, and fruit quality assessment.

Source	Operation	Model	Reported Performance Metrics
Jafary et al. [50]	Raspberry phenology-stage detection for growth monitoring and yield estimation	YOLOv8, YOLOv10, RT-DETR, Faster R-CNN, Mask R-CNN; RGB	mAP@0.5 = 71.7%; Precision = 72.1%; Recall = 66.8%; F1 = 69.3%; mAP@0.5:0.95 = 54.8%
Sudars et al. [51]	Raspberry developmental-stage detection for phenotyping and yield estimation	YOLOv5; RGB	mAP@0.5 = 80.9%; mAP@0.5:0.95 = 53.7%; inference time = 0.02 s/image
Naranjo-Torres et al. [52]	Detection of raspberry diseases and defects for post-harvest quality control	Faster R-CNN; Inception-v3, SqueezeNet, ResNet50/101, VGG16/19; RGB	Precision up to 100%; Accuracy = 66.7–100%; class-specific AP = 27–55%; ≈30 s/tray
Quintero Rincón et al. [53]	Raspberry disease and defect detection for post-harvest quality control	Faster R-CNN; statistical features + ANN; RGB	Average Faster R-CNN accuracy = 91.2%; class-specific accuracy = 75–100%; statistical methods = 81.0–84.5%
Williams et al. [54]	High-throughput phenotyping of plant architecture and spectral traits	VNIR hyperspectral imaging; PCA, vegetation indices, mixed models, QTL mapping	Cane density–NDRE $r = 0.789$; maximum spectral QTL LOD = 12.4
Williams et al. [46]	Detection of raspberry responses to biotic and abiotic stress	VNIR hyperspectral imaging; spectral ratios, PCA, REML/ANOVA	R469/R523 showed the strongest genotype $\times$ treatment response; spectral ratios correlated with growth and physiological traits

RGB-based computer vision has been used mainly for monitoring fruit development and estimating yield-related traits. Jafary et al. [50] introduced Raspberry PhenoSet, in which seven developmental stages from floral buds to mature fruit were annotated and linked to expected time to harvest. The dataset was evaluated using several object-detection models and provided a basis for phenological monitoring and yield forecasting. The approach was later extended to vertical farming environments [55], and Jafary et al. [18] used developmental-stage information to estimate yield and forecast harvest up to 28–33 days in advance. Sudars et al. [51] similarly used YOLOv5 to distinguish developmental stages of raspberry and Japanese quince fruit, demonstrating the potential of stage-specific detection for phenotyping, yield estimation, and berry-size assessment.

Computer vision has also been applied to raspberry fruit quality assessment. Naranjo-Torres et al. [52] used Faster R-CNN-based detection to identify albinism, fungus-rust, attached peduncles, and overripeness under controlled post-harvest imaging conditions. Quintero Rincón et al. [53] investigated the same defect classes using the Raspberries-LITRP image database and compared deep-learning detection with statistical feature-based classification. These studies were conducted after harvest rather than under field conditions, but they provide relevant examples of automated recognition of fruit condition and visible defects that may also inform future robotic inspection systems.

Hyperspectral imaging has been investigated for broader assessment of plant condition and phenotypic variability. Williams et al. [54] showed that spectral traits were associated with characteristics such as cane density, plant architecture, chlorophyll content, and plant health, supporting the use of hyperspectral data for high-throughput raspberry phenotyping. In a subsequent study, Williams et al. [46] examined spectral responses to *Phytophthora rubi*, vine weevil, and different water-availability treatments. Several spectral ratios were associated with plant growth and physiological traits, although the individual causes of stress could not always be distinguished reliably.

Taken together, the monitoring studies show a relatively high level of raspberry specificity, as the studies reviewed in this section were conducted directly on raspberry crops [18,46,50–54]. However, they address different biological targets, sensing modalities, and operating conditions and should therefore not be ranked directly according to their reported performance metrics. RGB-based developmental-stage detection has been applied to phenological monitoring, yield estimation, and harvest forecasting [18,50,51], whereas hyperspectral imaging has been used for broader assessment of plant condition, phenotypic variability, and responses to biotic and abiotic stress [46,54]. A key remaining step for robotic deployment is validation across different cultivars, seasons, production systems, and field conditions, since cultivar variability, seasonal changes in plant appearance, and environmental conditions can affect perception performance [21].

3.3. Targeted Spraying and Related Precision Applications

Targeted spraying represents a promising application for extending the utilisation of robotic platforms beyond harvesting. By combining crop perception with accurate positioning of a spraying actuator, treatments can be applied selectively to individual plants or affected canopy regions, potentially reducing unnecessary pesticide use [56–60]. This level of spatial selectivity is particularly relevant to high-value horticultural crops with complex canopies and repeated crop-protection requirements. From the perspective of multifunctional robotics, spraying is also attractive because the mobile platform, robotic arm, and core perception infrastructure can potentially be shared with other operations, while only the task-specific end-effector and control strategy are adapted [14].

Robotic Solutions for Targeted Spraying and Related Precision Applications

No robotic-arm system specifically developed for targeted spraying in raspberry production was identified. Therefore, systems developed for other horticultural crops were considered where their robotic architecture, perception methods, spraying end-effectors, or control strategies were potentially transferable to raspberry production. Related precision applications, including chemical blossom thinning and targeted pollination, were also included when they demonstrated comparable perception–localisation–application workflows. Technical characteristics are summarised in Table 5 and reported operational performance in Table 6. Because the systems differ substantially in crop, treatment objective, robotic configuration, and evaluation protocol, the reported performance values should not be interpreted as direct comparisons. The performance indicators reported in Table 6 reflect different treatment objectives and robotic configurations, ranging from trajectory accuracy and selective spraying to chemical reduction and targeting success. These values therefore illustrate the capabilities of individual systems but should not be interpreted as directly comparable measures of overall performance.

Table 5. Technical characteristics of robotic target spraying systems and related precision applications.

Source	Model	Vehicle	Robot	Communication	End-Effector	Sensors	Computing	Control	Autonomy
Vatavuk et al. [61]	Task-space linear MPC; QP	Custom flipper-tracked mobile base	Kinova Gen3 (Kinova Inc., Boisbriand, QC, Canada); 7 DoF	ROS; Ethernet; CAN bus; USB	Spray nozzle; pump; 30 L tank	Joint encoders; track encoders; odometry; OptiTrack (NaturalPoint Inc., Corvallis, OR, USA)	Intel NUC 10; i7-10710U; Ubuntu 20.04	Task-space MPC; proportional control; QP trajectory tracking	Semi-autonomous
Krklješ et al. [14]	U-Net/U-Net++; YOLOv5; UNet++-ResNet50; K-means; ALNS-k-opt	Customized 4WD HK1500-DM6-E UGV; DJI Phantom 4 Multispectral UAV (DJI, Shenzhen, China)	UR5e; 6 DoF	ROS; MQTT; REST API; 4G/Wi-Fi; BLE	Interchangeable soil sampler + MiniLab; low-volume spray nozzle; 2× Plant-O-Meter (Bitgear, Belgrade, Serbia)	RTK; IMU; OS1-32 LiDAR (Ouster, Inc., San Francisco, CA, USA); D435i; OAK-D RGB-D (Luxonis Holding Corporation, Denver, CO, USA); multispectral UAV camera; soil and optical sensors	Jetson Xavier NX (NVIDIA Corporation, Santa Clara, CA, USA); Raspberry Pi 4B (Raspberry Pi Ltd., Cambridge, UK); Arduino Due; ESP32 (Espressif Systems, Shanghai, China)	Autonomous navigation; LiDAR obstacle avoidance; ALNS routing; MoveIt; TF	Semi-autonomous
Oberti et al. [60]	Spectral indices; region growing; rule-based classification	Wheeled trailer platform	CROPS manipulator; 6 DoF	ROS; UDP; CAN; Ethernet	Precision sprayer; 150–200 mm spot	R-G-NIR multispectral camera; wheel encoder	Sensing PC; industrial PC; xPC Target	IK; trajectory planning; self-collision check; target queue	Fully autonomous spraying
Mu et al. [62]	Mask R-CNN-ResNet101; coordinate transformation	Clearpath Husky A200 UGV	Fixed extended spraying arm; DoF N/R	ROS	Solenoid valve; TeeJet AIXR11003 flat-fan nozzle (TeeJet Technologies, Glendale Heights, IL, USA); 4-gal sprayer	ZED2 stereo camera (Stereolabs, San Francisco, CA, USA); RTK-GPS	Onboard laptop; specifications N/R	Flower detection; georeferencing; GPS-based targeting; nozzle control	Semi-autonomous
Gao et al. [63]	YOLOv8m; preferential flower selection; Euclidean-distance targeting	Crawler chassis	Mechanical arm; model/DoF N/R	TCP/IP; USB; serial bus	8-nozzle air-liquid sprayer	RealSense D435 RGB-D	Jetson Xavier NX	Multinozzle targeting; coordinate transformation; selective nozzle actuation	Semi-autonomous

Table 6. Reported operational performance of robotic targeted spraying systems and related precision applications.

Source	Crop	Operation	Success	Time	Additional Quantitative Performance Metrics
Vatavuk et al. [61]	Grapevine	Canopy spraying	N/R	N/R; 0.3 m·s ^{−1} spray trajectory	RMS trajectory error = 4.32 mm under vineyard conditions; maximum error = 22.16 mm
Krklješ et al. [14]	Blueberry	Soil sampling and analysis; targeted weed spraying; plant monitoring	N/R	5–6 min analysis ^{−1} ; 30–60 s·spray ^{−1} ; 1 s·measurement ^{−1}	Herbicide use reduction = 50–60%; weed IoU = 0.78; spraying capacity = 135–270 m ² ·h ^{−1}
Oberti et al. [60]	Grapevine	Selective fungicide spraying	85–100% disease area sprayed	N/R	Pesticide reduction 63–84%; false-positive spray area 5–20%
Mu et al. [62]	Apple	Chemical blossom thinning	N/R	10.6 s·tree ^{−1}	Detection P/R/F1/IoU 93.8/91.2/92.5/86.1%; 66.7% chemical reduction vs. ABS; georeferencing RMSE 1.2–6.8 cm
Gao et al. [63]	Kiwifruit	Targeted pollination	93.4% targeting	1.2 s·flower ^{−1}	mAP 98.4%; detection success 98.9%; fruit set 88.9%

Note: N/R denotes Not Reported.

The reviewed systems demonstrate different approaches to robotic targeted spraying. In robotic arm-based spraying systems, the robotic arm is used to position the application nozzle relative to the canopy or detected target. Vatavuk et al. [61] focused primarily on coordinated mobile-manipulator control for vineyard spraying (Figure 5a), whereas Oberti et al. [59,60] integrated multispectral disease detection, target localisation, robotic positioning, and selective fungicide application within a complete perception-to-treatment workflow. Their robotic system is shown in Figure 5c. The latter system demonstrated that crop-protection treatments can be spatially restricted to detected disease regions, with substantial reductions in pesticide use reported in comparison with conventional application (Table 6).

Modular platform architectures provide a further route towards integrating targeted spraying into multifunctional agricultural robots. Krklješ et al. [14] combined a mobile platform, robotic arm, shared sensing and navigation infrastructure, and interchangeable agricultural modules for blueberry production (Figure 5b). In this configuration, targeted weed spraying represented one of several operations performed using the same underlying platform. This approach is particularly relevant to raspberry production because spraying could potentially share the mobile base, robotic arm, perception, and control infrastructure with monitoring, harvesting, or cane-management operations.

Related precision applications show that similar sensing and targeting approaches can also be used for operations other than crop protection. Mu et al. [62] combined flower detection and georeferencing with selective chemical blossom thinning (Figure 5d), while Gao et al. [63] integrated RGB-D flower localisation with selective multi-nozzle actuation for targeted pollination (Figure 5e). Although these systems differ from conventional robotic-arm pesticide spraying and use different robotic configurations, both rely on accurate target detection, localisation, and selective application. These functions are also relevant to raspberry production, where a robotic platform would require reliable target

localisation, accurate positioning of the application device, and selective actuation under field conditions.

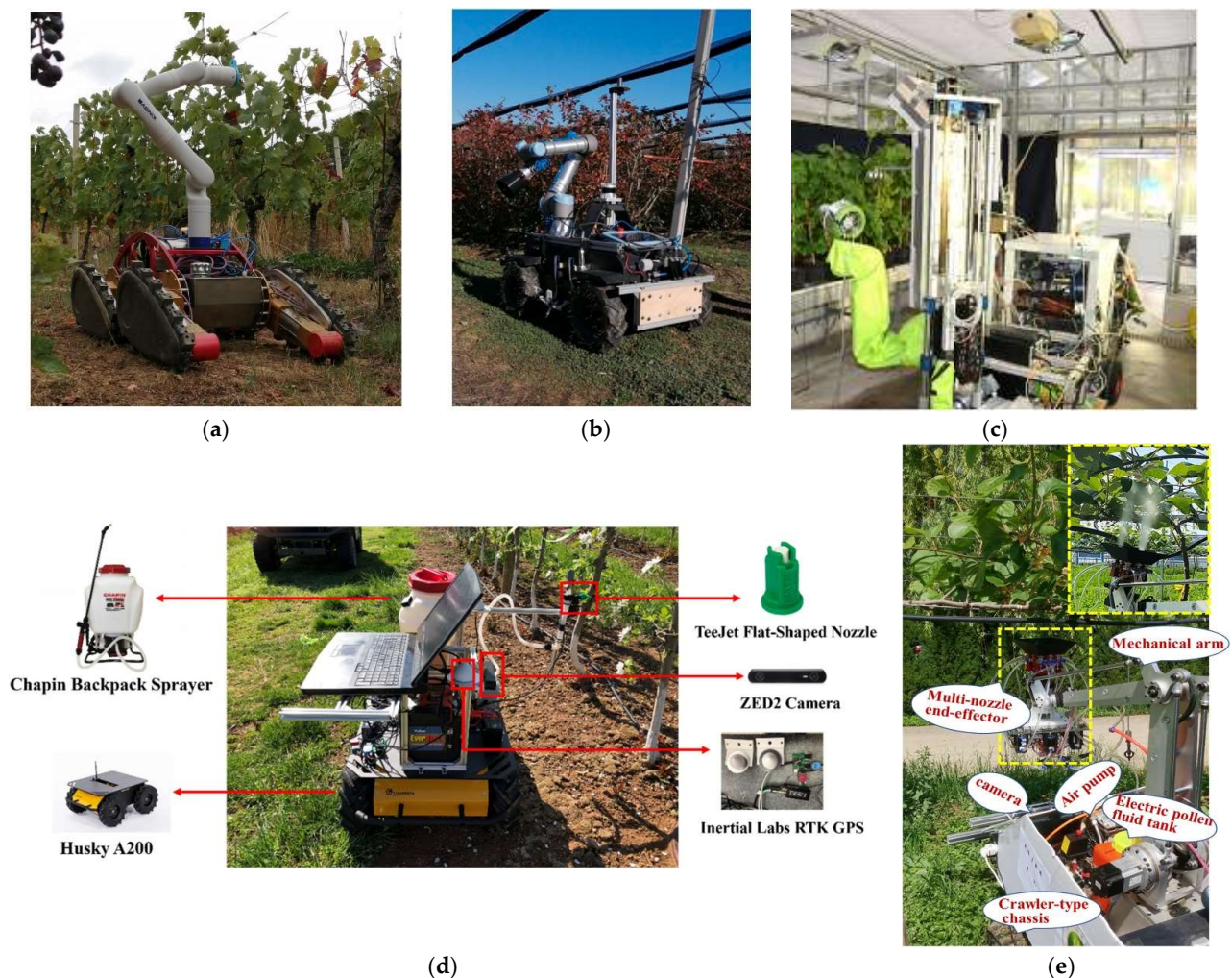


Figure 5. Representative robotic systems for targeted spraying and related precision application operations: (a) Vatauvuk et al. [61]; (b) Krklješ et al. [14]; (c) Oberti et al. [60]; (d) Mu et al. [62]; and (e) Gao et al. [63].

The transferability of these systems to raspberry production is therefore uneven. Shared mobile-platform architecture, target localisation, robotic arm positioning, and selective actuator control are broadly transferable at the system level, as demonstrated in robotic spraying and related precision-application systems developed for blueberry, grapevine, apple, and kiwifruit [14,60–63]. In contrast, crop- and target-specific perception models, spray geometry, application parameters, and treatment efficacy require raspberry-specific validation because they depend on the crop structure, target characteristics, and treatment objective [14,60–63]. For targeted application, technical performance such as target detection, localisation, and nozzle positioning should therefore be complemented by treatment-level validation. The reviewed studies evaluated not only targeting performance but also outcomes such as sprayed disease area, pesticide or chemical reduction, false-positive spray area, fruit set, and pollen use [60,62,63]. These results indicate that successful target detection and actuator positioning alone are insufficient to demonstrate effective treatment. Application quality, off-target effects, and biological efficacy should also be verified under variable canopy and environmental conditions [21,58].

3.4. Harvesting

Harvesting is the most extensively studied robotic operation in raspberry production. Its automation requires reliable fruit detection and maturity assessment, accurate localisation, robotic-arm positioning, and gentle fruit detachment. The following sections review both perception methods and complete robotic harvesting systems developed for raspberries.

3.4.1. Fruit Detection and Maturity Assessment

Reliable fruit detection is a key requirement for the automation of raspberry harvesting, as it provides the information needed to identify harvestable fruit and distinguish it from surrounding plant material [23,64,65]. In practice, detection is often combined with the assessment of fruit maturity, since selective harvesting requires not only the localisation of individual berries but also an indication of whether they have reached an appropriate stage for harvest [65,66]. This is particularly challenging in raspberry crops because fruits may be partially occluded by leaves or other berries, occur at different stages of development within the same canopy, and be observed under variable lighting and background conditions [66–68].

The studies considered in this section are specific to raspberries and include both field and controlled-environment applications, as well as selected post-harvest approaches relevant to fruit maturity assessment. An overview of the investigated methods and their reported performance is provided in Table 7, while the individual studies are discussed in more detail below.

Table 7. Overview of computer vision approaches for raspberry fruit detection, maturity assessment, and harvest-related applications.

Source	Operation	Model	Quantitative Performance Metrics
Strautiņa et al. [69]	Raspberry developmental-stage detection and phenotyping for yield estimation	RaspberrySet dataset; YOLO-format annotations; RGB	No model performance metrics reported; dataset: 2039 RGB images, 46,659 annotations across five classes.
Ling et al. [68]	Raspberry maturity detection across three stages under varying weather and lighting conditions	HSA-YOLOv5s; improved HSV colour-space transformation + adaptive dataset homogenisation; RGB	mAP = 97.01%; Recall = 93.36%; class AP = 95.01–98.74%
Alkhudaydi [70]	Raspberry ripeness and developmental-stage detection for crop monitoring and yield estimation	Four YOLOv8 variants; 15 hyperparameter configurations; RaspberrySet RGB dataset	mAP@0.5 = 78.6%; mAP@0.5:0.95 = 47.5%
Zhang et al. [64]	Ripe raspberry and stalk detection, stalk pose estimation and segmentation, and optimal cutting-point determination for robotic harvesting	Improved YOLOv8n for day/night detection; YOLOv8n-pose; YOLOv8n-seg; RGB-D	Day: mAP@0.5 = 83.6%, Precision = 81.0%, Recall = 80.7%, 167.0 fps. Night: mAP@0.5 = 93.4%, Precision = 88.4%, Recall = 90.7%, 153.8 fps.
Mekhalfi et al. [71]	Post-harvest raspberry ripeness grading and instance segmentation into five quality grades in an industrial environment	YOLOv8n-seg; RGB	Best segmentation: Precision = 67.9%; Recall = 68.0%; mAP@0.5 = 65.5%; mAP@0.5:0.95 = 53.9%. Detection: mAP@0.5 = 65.4%; mAP@0.5:0.95 = 58.2%.

Table 7. Cont.

Source	Operation	Model	Quantitative Performance Metrics
Luo et al. [67]	Red raspberry maturity detection in field and greenhouse environments for intelligent harvesting	Improved YOLOv11n with HCSA attention, DWR and DySample; RGB	Precision = 92.2%; mAP@0.5 = 93.4%; mAP@0.5:0.95 = 79.8%; F1 = 89.0%; unripe mAP@0.5 = 92.5%; ripe mAP@0.5 = 94.3%;
Han et al. [72]	Post-harvest raspberry maturity detection and fine-grained classification into five ripeness stages	YOLO-CG-CPCA based on YOLOv8s; C2f-CG + CPCA attention + WIoUv2; RGB	AP = 96.6%; Recall = 96.8%; mAP@0.5 = 98.8%; 7.95 MB parameters; 254.8 fps. mAP@0.5
Buczyński et al. [66]	Detection of harvest-ready red, yellow, and purple raspberry fruits under field conditions	YOLOv8s, YOLOv9s, YOLOv10s, YOLO11s, YOLO12s; RGB	Mixed-colour dataset: Precision = 89.6%, Recall = 87.4%, mAP@0.5 = 94.2%, mAP@0.5:0.95 = 66.3%, F1 = 88.5%. Inference: up to 247 fps on RTX 5080; up to 77.5 fps on Jetson Orin NX with TensorRT.
Zhao et al. [73]	Black raspberry ripeness detection across four maturity stages in complex greenhouse environments for selective harvesting	SDGD-YOLO based on YOLOv13n; StarNet backbone + DySample + Soft-NMS-GIoU + knowledge distillation; RGB	Precision = 91.0%; Recall = 71.8%; F1 = 80.68%; mAP@0.5 = 81.7%; mAP@0.5:0.95 = 68.7%

Several studies have focused on distinguishing raspberry developmental or maturity stages from RGB images. Strautiņa et al. [69] introduced RaspberrySet, a field-acquired dataset covering buds, flowers, and ripe and unripe fruit under different weather conditions and viewing angles, providing a basis for subsequent detection and phenotyping studies. Alkhudaydi [70] later evaluated YOLOv8 models using this dataset, showing that developmental-stage detection can support crop monitoring and ripeness assessment. Ling et al. [68] addressed the additional problem of variable illumination by combining YOLOv5 with colour-space adaptation to distinguish unripe, near-ripe, and ripe raspberries under changing field conditions.

More recent work has focused directly on harvest-ready fruit detection under conditions relevant to robotic harvesting. Luo et al. [67] developed a lightweight model for distinguishing ripe and unripe raspberries in greenhouse and outdoor environments, with particular attention to occlusion, complex backgrounds, and uneven illumination. Buczyński et al. [66] compared several YOLO architectures for detecting harvest-ready red, yellow, and purple raspberries under field conditions and also evaluated real-time deployment on embedded hardware. Zhao et al. [73] extended maturity detection to four ripeness stages in black raspberry and designed the model for operation under fruit overlap, foliage occlusion, and scale variation. In recent detection methods, robustness and computational efficiency are increasingly considered together with classification accuracy for practical robotic deployment.

For robotic harvesting, fruit detection must ultimately be linked to a physical target for the robotic arm or end-effector. Zhang et al. [64] addressed this requirement by combining ripe-fruit and stalk detection with pose estimation, segmentation, RGB-D localisation, and cutting-point determination. The detected stalk position was transformed into world coordinates for subsequent end-effector positioning, providing a direct connection between visual perception and robotic manipulation. The comparison between daytime and nighttime operation also showed the influence of illumination stability on detection performance.

Post-harvest studies provide additional information on fine-grained maturity and quality assessment, although their operating conditions differ from those encountered

during field harvesting. Mekhalfi et al. [71] used instance segmentation to classify raspberries into five quality grades in an industrial conveyor environment, while Han et al. [72] investigated five maturity stages under controlled illumination. These approaches are therefore more directly applicable to automated grading and sorting, but they also illustrate the level of visual discrimination that may be useful when future harvesting systems need to distinguish between closely related maturity stages.

The high detection metrics reported in several raspberry studies should be interpreted in the context of their individual datasets, imaging conditions, and evaluation protocols [64,66–73]. Performance above 90% in mAP, precision, or recall within a given study does not necessarily demonstrate equivalent robustness across unseen cultivars, farms, seasons, illumination conditions, camera viewpoints, or canopy structures. Some studies explicitly considered more variable conditions, including changing weather and illumination [68], field and greenhouse environments [67], field-acquired images of different raspberry fruit colours [66], and complex greenhouse scenes with occlusion and scale variation [73]. In contrast, other studies were conducted under controlled post-harvest or industrial imaging conditions [71,72]. Within the reviewed literature, systematic validation across multiple farms, seasons, and production environments remains limited. Consequently, the values reported in Table 7 should be interpreted as study-specific performance indicators rather than as a direct ranking of model robustness.

3.4.2. Robotic Solutions for Raspberry Harvesting

The development of complete robotic systems for raspberry harvesting remains limited. Only two implemented solutions specifically intended for raspberry harvesting were identified in the reviewed sources. The system presented by Junge et al. [23] was developed and experimentally evaluated as a research platform, whereas the Fieldwork Robotics system [74] represents a commercial solution developed for field harvesting.

Table 8 summarises the main technical characteristics of the identified systems, including the vehicle platform, robotic arm, end-effector, sensing equipment, computing hardware, control architecture and level of autonomy. Table 9 presents the available information on their harvesting approach and operational performance, including harvesting success, throughput, fruit damage and other reported performance metrics. Although Table 9 summarises harvesting success, operational rate, fruit damage, and other reported indicators, the two systems were evaluated under different experimental and deployment conditions. The reported values should therefore be interpreted as system-specific performance indicators rather than as a direct benchmark comparison.

Table 8. Technical characteristics and system architecture of robotic solutions for raspberry harvesting.

Source	Vehicle	Robot	Communication	End-Effector	Sensors	Computing	Control	Autonomy
Fieldwork Robotics [74]	Autonomous wheeled platform	4 picking arms	N/R	Custom selective gripper	3D global + gripper cameras; sensors	N/R	Real-time fruit selection and harvesting	Fully autonomous
Junge et al. [23]	Husarion Panther 4WD	UR5; 6 DoF	U2D2 (Dynamixel)	Force-controlled parallel-jaw gripper; silicone fingers	OAK-D; Pi Camera; ToF; 2 × load cells	Control PC; Jetson Nano; Arduino Nano Every	PID force control; visual servoing; Cartesian alignment	Semi-autonomous

Note: N/R denotes Not Reported.

Table 9. Operational performance of robotic systems for selective raspberry harvesting.

Source	Model	Operation	Success	Operational Rate	Damage	Additional Quantitative Performance Metrics
Fieldwork Robotics [74]	Proprietary AI/ML; 3D vision	Selective harvesting	N/R	$\approx 1 \text{ kg} \cdot \text{h}^{-1}$	N/R; human-comparable quality	4 arms; target $>4 \text{ kg} \cdot \text{h}^{-1}$; commercial field deployment
Junge et al. [23]	HSV thresholding; CHT	Selective harvesting	80% harvest; full pipeline 4/7	N/R	60% none; 20% minor; 12% damage	Localisation $\Delta x / \Delta y = 1.5/6.1 \text{ mm}$; 8% no harvest

Note: N/R denotes Not Reported.

A robotic system for selective raspberry harvesting, originating from research by Martin Stoelen and subsequently developed and commercialised by the University of Plymouth spin-out Fieldwork Robotics [74] has evolved from early prototypes into a fully autonomous multi-arm harvesting platform. Earlier prototypes evolved from a single-arm system requiring approximately 60 s to harvest and deposit one fruit to a four-arm platform achieving approximately $1 \text{ kg} \cdot \text{h}^{-1}$ during commercial trials in Portugal in 2022 [75]. The system was subsequently redesigned, particularly its sensors and grippers [76], to improve fruit detection and reduce harvesting time [74]. The current Fieldworker 1 (Fieldwork Robotics Ltd., Cambridge, UK) (Figure 6) uses four harvesting arms together with AI-enhanced sensing and spectral information for ripeness assessment. According to Fieldwork Robotics, the system is designed to achieve harvesting speed and fruit quality comparable to human pickers, although detailed quantitative performance data for the current generation have not been published [74].

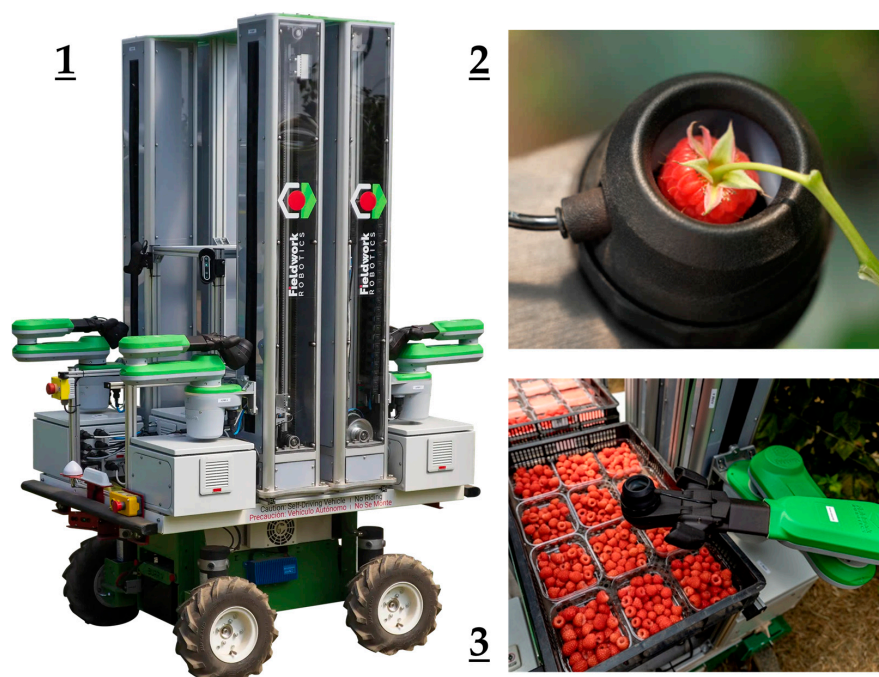


Figure 6. Commercial robotic system developed by Fieldwork Robotics for selective raspberry harvesting: overall configuration of the multi-arm harvesting platform [74] (1), selective raspberry picking end-effector [76] (2), and fruit-handling operation [74] (3).

Junge et al. [23] presented a semi-autonomous system (Figure 7) for selective raspberry harvesting, in which the mobile platform was manually positioned in front of the crop, while fruit localisation, visual alignment, grasping, and force-controlled harvesting were performed autonomously. The harvesting controller was evaluated separately on 25 fruits, achieving 80% minor-to-no-damage harvests, including 60% without visible damage and 20% with only minor damage; 12% of the fruits were damaged and 8% were not harvested. When the complete autonomous sequence combining visual servoing and harvesting was evaluated, four of seven harvesting attempts were successful. The central contribution of the study, however, was the development of a sensorised physical twin of a raspberry for laboratory-based controller development (Figure 8) [23,77]. The physical twin reproduced key characteristics of the fruit–receptacle interaction and incorporated load cells and a pressure sensor to measure forces during grasping and detachment. Human harvesting demonstrations were used to obtain reference force profiles and automatically tune the force controller. Importantly, the resulting controller was subsequently transferred from the laboratory to real raspberry plants without additional field tuning, demonstrating a Lab2Field approach that reduces the dependence of robotic harvesting development on seasonal access to real fruit.

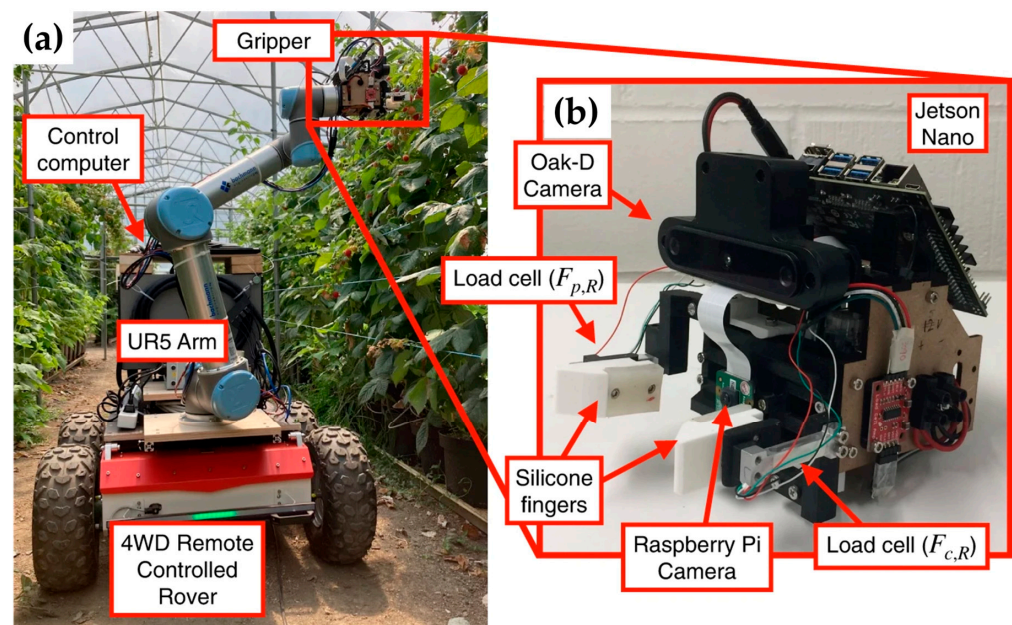


Figure 7. Lab2Field robotic raspberry harvesting platform: (a) mobile robotic arm operating in the field and (b) sensorised gripper with integrated vision, force sensing and onboard computing [23,77].

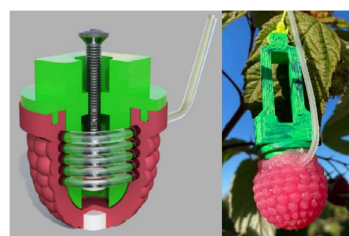


Figure 8. Sensorised physical twin of a raspberry developed for laboratory-based controller testing: conceptual design and physical implementation [23].

The two raspberry harvesting systems also represent different levels and forms of technological maturity. Fieldwork robotics [74] provides evidence of commercial field deployment and multi-arm operation but publishes only limited quantitative data for the

current generation. In contrast, Junge et al. [23] provide detailed experimental measurements, although these were obtained on a research platform with a manually positioned mobile base and a small number of full-pipeline trials. These systems therefore complement rather than directly benchmark one another: one demonstrates commercial deployment, while the other provides transparent experimental evidence on force-controlled fruit interaction and Lab2Field transfer.

A broader range of robotic-arm harvesting systems using fruit-grasping end-effectors has been reported for other delicate fruit crops. In the academic literature reviewed here, Brown and Sukkariéh [78] evaluated a UR5-based plum harvesting system with both rigid and soft grippers, demonstrating the use of interchangeable gripping mechanisms within a common robotic architecture. Commercial-sector development also includes the TX strawberry harvester from Advanced Farm Technologies, which combines an autonomous ground vehicle, image-based AI perception, and robotic arms equipped with fruit-picking grippers [79]. In addition, a patent originating from Root AI and currently assigned to Zordi and AppHarvest Technology describes a mobile vision-guided harvesting system in which one or more robotic arms are equipped with graspers and compliant fruit-handling elements intended to reduce damage to delicate produce [80].

3.5. End-Effector Solutions Applicable Across the Raspberry Production Cycle

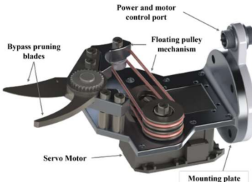
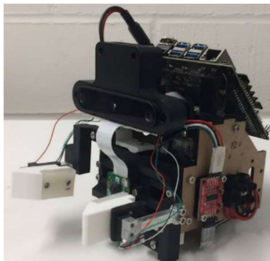
End-effectors provide the physical interface between a robotic system and the crop, and their design is therefore closely linked to the operation being performed [81,82]. Across the production cycle, different tasks require substantially different forms of interaction, ranging from targeted spray delivery and cane cutting to the handling and detachment of delicate fruit [12,31,60,82].

Only the harvesting end-effectors identified in this review were developed specifically for raspberry. End-effector concepts reported for spraying and pruning originate from related robotic applications in other crops but are included because their operating principles are relevant to comparable tasks in raspberry production. Table 10 summarises the identified end-effector types, their working principles and the main technical parameters reported for each design.

For spraying and pruning, the end-effector is primarily required to position and execute a specific treatment accurately. Oberti et al. [60] developed an air-assisted precision sprayer that combined a confined spray pattern with robotic positioning for selective treatment of diseased grapevine regions. In contrast, Silwal et al. [31] used servo-driven bypass shears for selective cane removal. These systems illustrate the different mechanical requirements of crop-protection and pruning operations: spraying depends mainly on controlled application and nozzle positioning, whereas pruning requires sufficient cutting force and reliable placement of the plant structure between the blades.

Harvesting end-effectors place greater emphasis on compliant interaction with the fruit. Junge et al. [23] used a parallel-jaw gripper with silicone-covered fingers and load cells, allowing grasping and pulling forces to be monitored during raspberry harvesting. Furia et al. [83] followed a softer approach with the pneumatic GraspBerry gripper and interchangeable fingertips adapted to different fruit properties. Although both designs aim to reduce mechanical damage, they rely on different strategies: active force monitoring in the former and compliant contact surfaces in the latter.

Table 10. Overview of end-effector designs for harvesting and other robotic operations relevant to raspberry production.

Source	End-Effector Image	End-Effector Type	Working Principle	Technical Parameters
Oberti et al. [60]		Air-assisted precision sprayer	Air-assisted spot spraying	3.5 kg; 18 mL·min ⁻¹ ; 350 kPa; fan 0–9500 rpm; spray Ø 150–200 mm
Silwal et al. [31]		Custom bypass pruning shears	Servo-driven bypass cutting with pulley transmission	0.45 kg; 8 Nm servo; MA = 3; blade opening = 38 mm; ~320 N cutting force for Ø 8 mm cane; tested cane Ø = 5–11 mm
Junge et al. [23]		Force-controlled parallel-jaw gripper	Force-controlled grasping and pulling	2× silicone-covered fingers; 2× 500 g load cells; Dynamixel XM430-W210-R; rack-and-pinion drive
Fujinaga [13]		Scissor-type grasping and cutting mechanism	Simultaneous grasping and cutting	Interchangeable; 8-bolt mounting; software-adjustable actuator range
Furia et al. [83]		GraspBerry soft pneumatic gripper	Soft pneumatic grasping; interchangeable frictional fingertips	DA-based self-healing polymer; 3 interchangeable fingertip patterns; human-inspired distal phalanx
Fieldwork Robotics [74,84]	(a) 	Two-jaw mechanical gripper	Mechanical grasping and detachment of individual raspberry fruits	Two opposing gripping jaws; camera-assisted fruit localisation; early prototype configuration
	(b) 	Inflatable-membrane end-effector	Fruit enclosure + pneumatic membrane grasping	Flexible inflatable membrane; variable entry aperture; internal fruit-receiving volume; tapered outer geometry

Fujinaga [13] demonstrated a different concept in strawberry harvesting by combining grasping and cutting within a single interchangeable mechanism. This approach reduces the need to separate fruit retention and detachment into two independent actions. Although the device was not evaluated for raspberry cane management, the combined grasp-and-cut principle may be relevant to operations in which the plant structure must be stabilised during cutting.

Commercial developments show a further shift in raspberry harvesting towards partial enclosure of the fruit rather than conventional finger-based grasping. Early prototypes developed by Fieldwork Robotics employed a two-jaw mechanical gripper for selective raspberry harvesting, as illustrated in Table 10 in (a) [84]. The company subsequently developed an end-effector based on a flexible inflatable membrane surrounding an internal fruit-receiving volume (Table 10 in (b)) [74,76]. After the fruit enters the opening, membrane inflation provides compliant retention. Compared with discrete-finger grippers, this concept increases the contact area and may reduce local pressure on the fruit. As the available information is based partly on commercial and patent sources, these developments are considered here primarily as examples of emerging end-effector concepts rather than as directly comparable performance data.

Across the raspberry harvesting concepts reviewed here, fruit damage is reduced through several complementary strategies. Junge et al. [23] used silicone-covered fingers together with load-cell-based force sensing, enabling grasping and detachment forces to be monitored and regulated during harvesting. Furia et al. [83] employed a soft pneumatic gripper with compliant, interchangeable fingertips, thereby reducing local contact pressure and adapting the contact interface to delicate fruit. A different strategy is represented by the Fieldwork Robotics end-effector [74,76], in which the fruit is partially enclosed by a flexible inflatable membrane, increasing the contact area and potentially reducing localised pressure. These systems therefore illustrate different routes to gentle raspberry manipulation rather than a single demonstrably superior end-effector architecture [23,74,76,83]. Direct tactile sensing beyond force or load measurement is not consistently reported among the raspberry-specific systems reviewed here and should therefore be regarded as a potential direction for future development rather than an established capability. Moreover, differences in fruit condition and ripeness, definitions of fruit damage, harvesting procedures, and experimental protocols prevent a direct quantitative ranking of the end-effectors summarised in Table 10.

3.6. Multifunctional Robotic Platforms

Current agricultural robotic systems increasingly integrate task-specific end-effectors with machine vision to perform individual operations, particularly harvesting [85–87], spraying [60,88–91], and pruning [31,40,42,92,93]. While these systems demonstrate the technical feasibility of robot-assisted crop management, most remain specialised for a specific task or crop. Extending the functionality of a single robotic platform across multiple operations therefore represents an important step towards more versatile and efficient agricultural automation [12,94]. Modular and reconfigurable architectures offer a potential solution by allowing robotic arms, end-effectors, sensing systems, or other application-specific components to be adapted or exchanged according to the required operation [95]. This concept is relevant to raspberry production, where management operations are distributed throughout the growing season and no single operation requires continuous use of the robotic platform throughout the year [13,14,94].

The approaches identified in the literature reviewed in this section can be broadly grouped into three complementary forms of flexibility. Multifunctional platforms retain a common mobile carrier while supporting different agricultural operations through task-

specific equipment. Modular systems retain the principal robotic architecture but allow application-specific components, particularly end-effectors or sensing modules, to be exchanged. Reconfigurable systems extend this concept further by allowing the kinematic structure of the robotic arm itself to be adapted to different crops or operating environments. Although these approaches differ in their degree of flexibility, they share the objective of reducing the need for completely separate robotic systems for individual tasks.

Bell [96] developed a multipurpose robotic system for kiwifruit orchards based on the autonomous multipurpose mobile platform. The platform served as a common mobile base for several orchard operations, including robotic harvesting, targeted pollination and autonomous navigation. Different task-specific hardware was integrated for harvesting and pollination, demonstrating a multifunctional platform concept in which the mobile carrier is shared while the crop-interaction components are adapted to the required operation. The work did not, however, describe a standardised quick-change interface between these application units.

A different form of adaptability was investigated by Levin and Degani [94], who proposed a task-based modular harvesting robotic arm whose kinematic structure could be reconfigured according to the crop and harvesting environment. The order and geometry of prismatic and revolute joint modules, including link length, could be modified to form different robotic arm architectures. This approach illustrates structural reconfigurability rather than multifunctionality across agricultural operations, but it demonstrates how a robotic arm can be adapted to crop-specific workspace and reachability requirements without developing a completely separate robotic arm.

Brown and Sukkarieh [78] focused on modularity at the end-effector level. Their harvesting platform incorporated a UR5 robotic arm together with a standardised hardware and software interface that allowed different grippers to be integrated without redesigning the overall system. The platform was experimentally evaluated with both rigid and soft grippers for plum harvesting. Although the system was not demonstrated across different agricultural operations, it provides a relevant example of how a common robotic architecture can accommodate crop- or task-specific manipulation hardware.

Fujinaga [13] developed a modular platform for small-scale agricultural applications in which a common mobile base and 6 DoF robotic arm could accommodate different harvesting mechanisms. A gripper-type end-effector was used for tomatoes, while strawberries were harvested using a scissor-type mechanism combining grasping and cutting. The end-effector could be exchanged without modification of the remaining hardware, with the main adjustments made through the actuator settings in the control software. The platform was also considered for additional operations such as truss pruning and crop monitoring, illustrating the potential for a shared robotic system to support a broader range of production tasks.

Krklješ et al. [14] demonstrated a more explicitly multifunctional modular architecture for blueberry production (Figure 9). Their unmanned ground vehicle integrated a UR5e robotic arm, RGB-D sensing, navigation and positioning equipment, and interchangeable agricultural modules. The platform supported soil sampling and analysis, targeted weed spraying and plant-health monitoring while retaining the same mobile carrier and core computational infrastructure. Among the systems considered here, this approach provides one of the clearest examples of distributing several production operations across a common robotic platform.

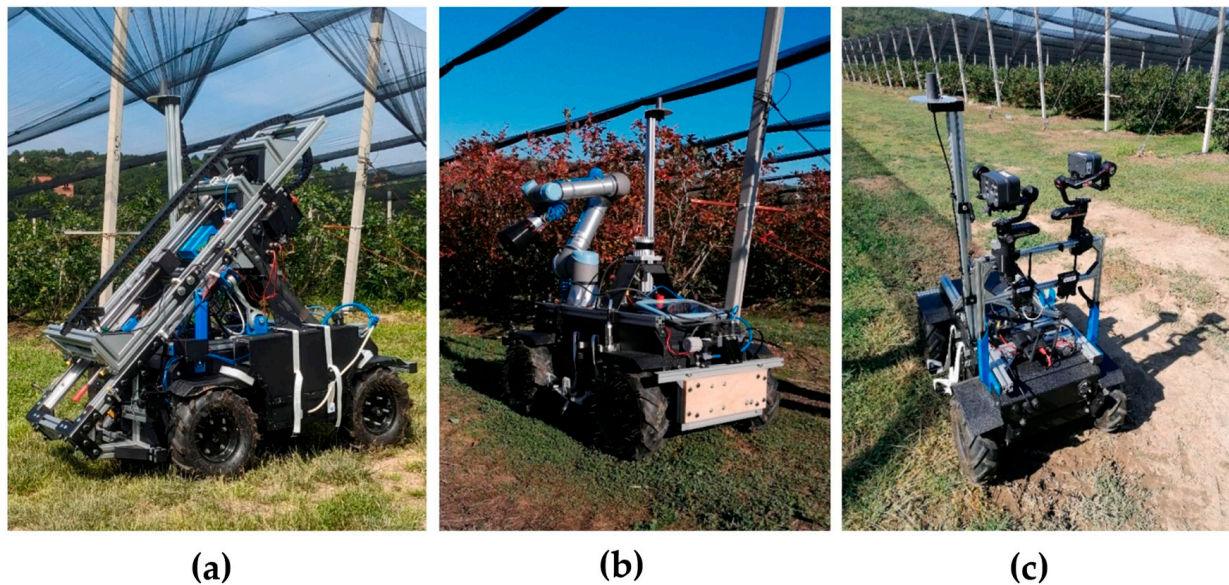


Figure 9. Customised UGV platform HK1500-DM6-E: (a) soil sampling and analysis module, (b) weed spraying module and (c) module for monitoring plant health status [14].

Across these platforms, the clearest evidence for multifunctionality comes from architectures that preserve a shared mobile, sensing, computing, and control core while exchanging task-specific application modules [13,14,96]. By contrast, reconfigurable robotic arms [94] or interchangeable grippers [78] improve system configurability but do not by themselves demonstrate multifunctionality across different agricultural operations. For raspberry production, the key transfer question is therefore not whether individual modules already exist, but whether they can be integrated through common mechanical, hardware, perception, and software/control interfaces [13,14,78]. Such integration must subsequently be validated across operations occurring at different phenological stages and under changing crop conditions [18,19,50,67–69].

4. Discussion

The reviewed studies show that many individual enabling technologies relevant to robotic operations in raspberry production have already been demonstrated, although they remain distributed across task-specific systems and, in several cases, across applications developed for other horticultural crops. As no raspberry-specific robotic platform has yet been demonstrated across multiple operations of the production cycle, it is important to consider these individual developments from a broader system-level perspective and in relation to their potential integration into a common multifunctional platform. On this basis, the Discussion is divided into three subsections: 4.1. Design Requirements for a Multifunctional Robotic Platform, 4.2. Challenges and Limitations of Multifunctional Robotic Platforms in Raspberry Production and 4.3. Future Research Directions.

4.1. Design Requirements for a Multifunctional Robotic Platform

The reviewed studies indicate several design requirements that are likely to be important for a robotic platform intended to operate across the raspberry production cycle. A suitable system would require a mobile base capable of operating within crop rows and supporting reliable positioning under variable field conditions [14,31,61]. The robotic arm should provide sufficient reach and flexibility to access targets within a dense canopy; 6 and 7 DoF configurations were the most common among the reviewed systems and appear well suited to this type of environment [13,14,23,31,60,61]. To extend the use of the platform beyond a single operation, the robotic arm should support interchangeable end-effectors

through a common mechanical and control interface, allowing tools for harvesting, pruning, spraying or other interventions to be exchanged without substantial modification of the underlying robotic system [13,14,78]. These design requirements and their relationships are synthesised in Figure 10.

Conceptual architecture for a multifunctional robotic platform in raspberry production

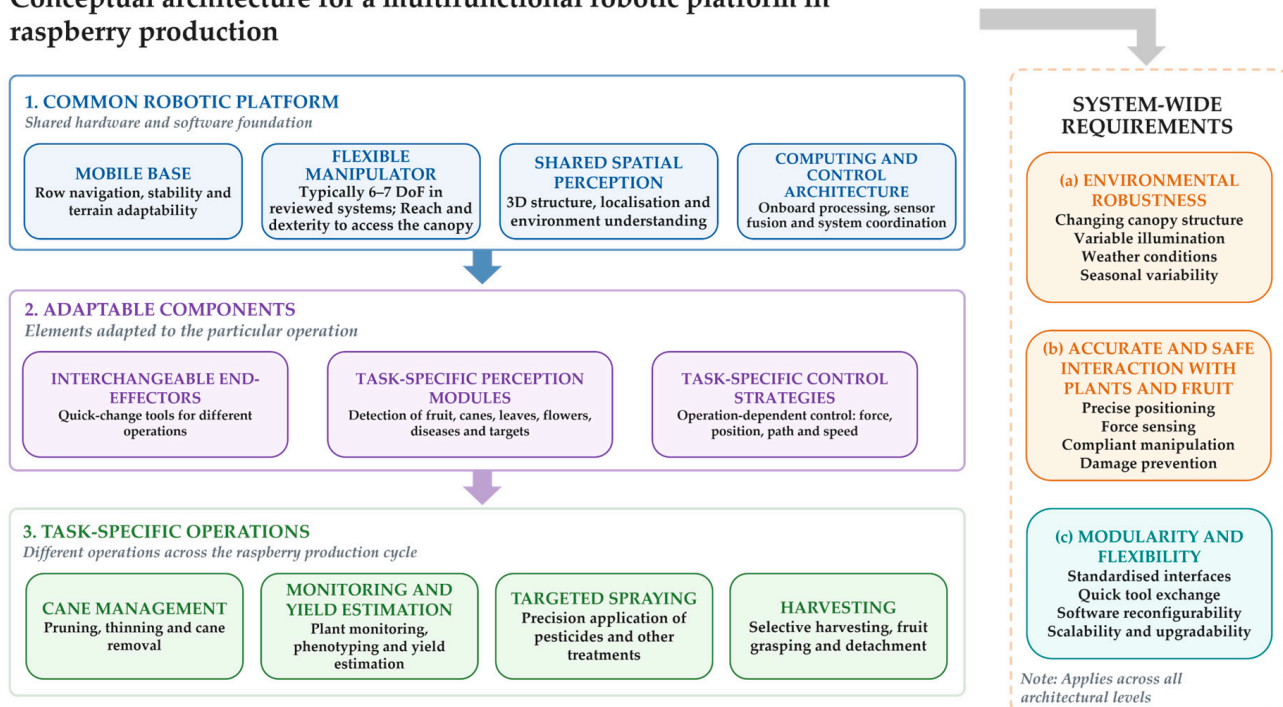


Figure 10. Conceptual architecture and system-wide design requirements for a multifunctional robotic platform supporting operations across the raspberry production cycle.

A shared perception architecture could provide the basis for several operations, with RGB-D sensing offering both visual information and spatial localisation of crop structures [13,14,64]. This shared sensing layer should be supported by a common computing and control architecture providing onboard processing, sensor fusion, and coordination between the principal robotic subsystems. This common sensing layer would, however, need to be complemented by task-specific perception and control functions according to the operation being performed. Harvesting requires particularly careful regulation of physical interaction with the fruit and may benefit from force sensing and compliant manipulation [23,83], whereas pruning and targeted spraying place greater emphasis on accurate tool positioning relative to branches, canes or localised treatment targets [41,42]. The system would also need to remain robust to seasonal changes in canopy structure, illumination, fruit development, and associated changes in target visibility and accessibility [50,67–69]. These requirements favour a modular architecture in which the mobile platform, robotic arm and core perception system remain largely common, while end-effectors, sensing functions and control strategies are adapted to individual operations [13,14,78]. Standardised interfaces, rapid tool exchange, software reconfigurability, and the possibility of future system expansion would further support the flexibility of such a platform.

Across the reviewed applications, the suitability of individual technologies depends on the information and physical interaction required by the task. RGB-based developmental-stage detection is directly applicable to phenological monitoring, yield forecasting, and harvest planning [18,50,51,55], whereas hyperspectral sensing provides richer information on plant condition and stress responses but requires more complex sensing and interpre-

tation [46,54]. For crop-contact operations, transferability is lower because harvesting requires compliant and force-regulated interaction with delicate fruit [23,83], while pruning additionally requires cane identification and structural interpretation, collision-free access, and accurate cutting [5,31,32,36,40–44]. Targeted spraying requires reliable target recognition and localisation, accurate application, and subsequent validation of spray deposition and biological efficacy [14,60–63]. Consequently, shared platform-level functions such as mobility, computing, navigation, communication, and generic motion planning appear more readily transferable across operations than crop-contact mechanisms, task-specific perception models, and control parameters, which require adaptation to raspberry morphology, phenology, and production conditions [13,14,78,94,96]. Accordingly, pruning and targeted spraying remain less mature than harvesting because they require additional task-specific validation. Pruning depends on reliable cane identification, structural interpretation, collision-free access, and accurate cutting. Targeted spraying must demonstrate not only accurate target localisation and nozzle positioning, but also adequate spray deposition and effective treatment under field conditions.

In Table 11, the reviewed application areas are compared in terms of raspberry-specific evidence, transferable technologies from other crops, and the main remaining task-specific gaps.

Table 11. Comparative synthesis of raspberry-specific evidence, transferable technologies from other crops, and task-specific requirements for a multifunctional raspberry robotic platform.

Operation/Technology Area	Raspberry-Specific Evidence	Transferable Evidence from Other Crops	Main Task-Specific Requirement and Transfer Gap
Cane management	Cane-type classification, cane detection and 3D localisation [5,36]	Grapevine and fruit-tree pruning systems [31,32,40–44]	Requires cane identity/structure interpretation, collision-free access and accurate cutting in a dense flexible canopy; robotic performance from grapevine/tree pruning is not directly transferable.
Crop monitoring and yield estimation	Substantial raspberry-specific RGB and hyperspectral studies [18,46,50–55]	General orchard/fruit monitoring principles	Perception can often be shared with other tasks, but robustness must be validated across cultivars, seasons and production systems.
Targeted spraying/precision application	No integrated raspberry robotic-arm spraying system identified	Grapevine, blueberry, apple and kiwifruit systems [14,60–63]	Platform, localisation and selective actuation are transferable; target recognition, spray parameters, deposition and biological efficacy require raspberry-specific validation.
Harvesting	Raspberry-specific perception, research harvesting and commercial deployment [23,64,66–74,77]	General soft-fruit harvesting principles	Highest raspberry-specific maturity; still limited by occlusion, illumination, delicate interaction, throughput and incomplete multi-site/multi-season validation.

Table 11. Cont.

Operation/Technology Area	Raspberry-Specific Evidence	Transferable Evidence from Other Crops	Main Task-Specific Requirement and Transfer Gap
End-effectors	Raspberry-specific harvesting grippers [23,74,76,83]	Pruning and spraying tools from other crops [13,31,60]	Crop-contact mechanism is strongly task-specific; common platform interfaces are more transferable than the end-effector itself.
Multifunctional platform	No raspberry-specific platform demonstrated across multiple operations	Modular/multifunctional platforms in blueberry, kiwifruit and other crops [13,14,78,94,96]	Need a shared core with standardised interfaces, task-specific modules and validation across phenological stages and operations.

At a more implementation-specific level, the reviewed systems show convergence around several recurring hardware and software components that could form a practical reference architecture for a future multifunctional raspberry platform. The UR5/UR5e family was repeatedly integrated into pruning, harvesting, and multifunctional robotic systems [23,31,32,40,78], while additional linear axes were used in pruning applications to extend the accessible workspace [31,32]. ROS was widely adopted as an integration framework for communication, perception, motion planning, and robotic control across pruning, spraying, and modular agricultural platforms [13,14,31,32,40,60,61]. It was frequently combined with established motion-planning frameworks and algorithms, including MoveIt, OMPL, and RRT-based planners [14,31,41,42]. This recurrence across independently developed systems suggests that a ROS-based modular software architecture, combined with a commercially available robotic arm and standardised interfaces, represents a technically mature starting point for integrating multiple operations on a common platform.

A similar implementation pattern is apparent in perception and onboard computing. RGB-D sensing was repeatedly used to combine visual recognition with spatial localisation, with Intel RealSense cameras appearing in pruning, modular crop-management, and targeted-application systems [13,32,41,42,63]. In raspberry-specific harvesting perception, RGB-D data were also used to transform detected fruit and stalk features into spatial information for subsequent robotic-arm positioning [64]. For onboard AI processing, NVIDIA Jetson platforms were used in multifunctional crop-management, targeted-application, and raspberry harvesting systems [14,23,63], while real-time raspberry detection was additionally evaluated on Jetson Orin NX hardware [66]. These implementations support the use of a shared RGB-D and GPU-accelerated perception layer as part of the common platform architecture, while allowing task-specific sensing to be added where required.

At the algorithmic level, the reviewed studies indicate that the perception layer should remain task-specific rather than rely on a single universal model. YOLO-family architectures were the most recurrent deep-learning approach across raspberry monitoring, maturity assessment, harvesting-related perception, pruning, and targeted treatment applications [13,18,35,39,41,42,51,63,64,66,68–73]. Depending on the operation, these models were used for object detection, segmentation, or pose estimation. For example, harvesting-related raspberry perception combined YOLOv8n-based detection, pose estimation, and segmentation with RGB-D localisation [64], whereas pruning-related systems used segmentation and detection models to identify plant structures and support cutting operations [41,42]. Alternative architectures, including Faster R-CNN, Mask R-CNN, RT-DETR, U-Net, and U-Net++, were also evaluated for monitoring, quality assessment, and crop-

specific segmentation tasks [14,18,52,53]. A future multifunctional platform could therefore retain common sensing and computing hardware while loading task-specific detection, segmentation, or pose-estimation models according to the required operation.

Based on the recurring implementation patterns identified in the reviewed studies, a multifunctional raspberry robotic platform could be built around a ROS-integrated robotic system, RGB-D perception, GPU-accelerated onboard computing, interchangeable task-specific end-effectors, and software-switchable vision models. The specific hardware and algorithms should remain adaptable to the requirements of each operation.

4.2. Challenges and Limitations of Multifunctional Robotic Platforms in Raspberry Production

The development and practical deployment of multifunctional robotic platforms in raspberry production is affected by technical, agricultural, robotic, and economic constraints. These constraints are closely related, as robotic performance depends on the interaction between the system, crop characteristics, field conditions, and operational costs. The main challenges identified in the reviewed studies are summarised in Figure 11 and discussed in the following sections.

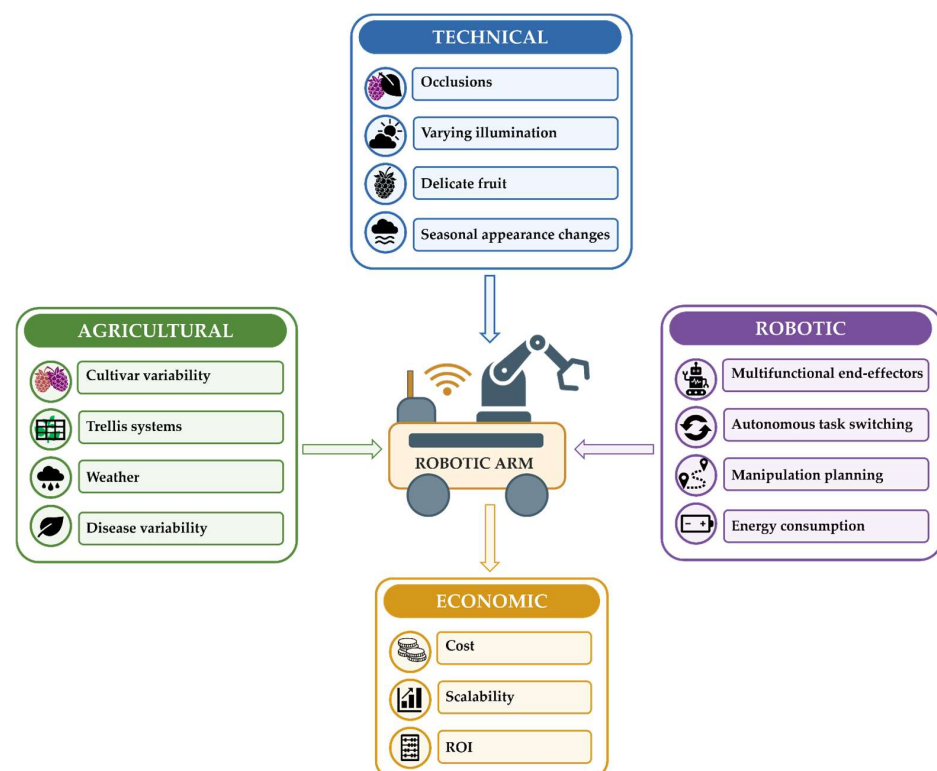


Figure 11. Key technical, agricultural, robotic, and economic challenges affecting the development and deployment of multifunctional robotic platforms in raspberry production.

4.2.1. Technical Challenges

Robotic operation in raspberry production is affected by several technical challenges related to perception and physical interaction with the crop. Occlusions caused by leaves, canes, and fruit clusters can limit reliable target detection and localisation, particularly in dense canopy regions [66,67,97]. Varying illumination, including changes in natural light, shadows, and reflections, may further reduce the robustness of vision-based perception under field conditions [68,98]. A particular challenge is associated with the delicate nature of raspberry fruit, which is highly susceptible to compression, abrasion, and deformation during manipulation. Harvesting therefore requires compliant end-effectors, accurate positioning, and appropriate force regulation to minimise fruit damage [23,83,99].

Raspberry-specific solutions have addressed these requirements through force-controlled grasping, as demonstrated by Junge et al. [23], and soft pneumatic grippers with adaptable contact surfaces, as proposed by Furia et al. [83]. In addition, seasonal changes in plant appearance alter canopy structure, target visibility, and the visual characteristics of relevant plant organs throughout the production cycle. Perception and manipulation systems must consequently remain reliable across different phenological stages and changing canopy conditions [100,101].

4.2.2. Agricultural Challenges

The practical deployment of robotic systems is further influenced by variability inherent to raspberry production. Cultivar variability affects fruit size, firmness, detachment characteristics, cluster architecture, and cane morphology, thereby changing both perception and manipulation requirements [102,103]. Trellis systems also influence target accessibility, available robotic arm workspace, and collision risk, particularly because many existing production systems have been designed primarily for manual rather than robotic operations [25,104]. Weather conditions, including wind, rain, humidity, and temperature, introduce additional uncertainty by causing plant movement and potentially affecting sensors, actuators, and onboard electronics [21,105]. Disease variability represents another challenge, as symptom appearance may differ according to pathogen, cultivar, infection stage, and environmental conditions and may overlap visually with nutrient deficiencies or natural senescence [52,58,106]. Several reviewed studies illustrate approaches to addressing these sources of variability, including adaptable gripper contact surfaces for differences in raspberry fruit properties proposed by Furia et al. [83] and illumination-adaptive image processing introduced by Ling et al. [68]. Other approaches include reconfigurable robotic arm architectures for different crop structures proposed by Levin and Degani [94], and hyperspectral monitoring of genotype-dependent stress responses demonstrated by Williams et al. [46]. Robotic systems intended for practical deployment must therefore be adaptable to biological variability, production architecture, and changing field conditions.

4.2.3. Robotic Challenges

A multifunctional robotic platform intended to operate throughout the raspberry production cycle must accommodate tasks with substantially different manipulation requirements. This creates a need for multifunctional or interchangeable end-effectors capable of supporting operations such as harvesting, pruning, targeted spraying, and crop inspection while maintaining low mass, mechanical simplicity, and safe interaction with plants [85,107]. Fujinaga [13] demonstrated this approach using replaceable task-specific end-effectors while retaining the same mobile platform, robotic arm, perception, power, and control infrastructure, whereas Krklješ et al. [14] integrated interchangeable agricultural modules within a common robotic platform. The platform must also support autonomous task switching, including adaptation of the end-effector, perception strategy, and control parameters according to the required operation and crop state [83,85,108]. Manipulation planning is particularly demanding in dense and deformable canopies, where the robotic arm must reach target structures while avoiding fruit, leaves, canes, and trellis components. Hizatate et al. [41,42] addressed this challenge through collision-aware motion planning combined with obstacle-model updates and end-effector-based target-position refinement. Finally, energy consumption is an important constraint for mobile platforms integrating robotic arms, sensing systems, onboard computing, and electrically, pneumatically, or vacuum-actuated tools [98,109,110]. Addressing these challenges requires robotic architectures that combine adaptable hardware with task-specific perception and control while retaining a common platform structure.

4.2.4. Economic Challenges

The commercial adoption of multifunctional robotic platforms ultimately depends on their economic viability. Cost includes not only the robotic arm itself but also the mobile platform, sensors, end-effectors, computing hardware, maintenance, and supporting infrastructure [111,112]. Krklješ et al. [14] demonstrated that combining several operations on a modular platform can provide task-level economic benefits, reporting reductions in herbicide use and soil-analysis costs in blueberry production. Scalability represents a further challenge, because performance demonstrated on individual plants or experimental rows must be transferred to commercial production environments while maintaining acceptable throughput, reliability, and failure rates [23,98]. The commercial deployment of the multi-arm raspberry harvesting system developed by Fieldwork Robotics [74] illustrates progress towards operational scaling, although this system remains specialised for harvesting. Return on investment (ROI) is particularly important in seasonal crops such as raspberry, where a robot designed for a single operation may remain underutilised for a substantial part of the year [111,113]. Multifunctional platforms could increase annual platform utilisation by distributing capital investment across several operations, including crop monitoring, targeted crop protection, harvesting, and cane management. Higher annual utilisation may improve the economic feasibility of robotic systems in raspberry production by reducing task-specific costs.

A quantitative ROI comparison between single-task and multifunctional raspberry platforms cannot currently be derived reliably from the reviewed evidence. The available studies do not report capital cost, maintenance, labour substitution, annual utilisation, throughput, service life, and operating costs using a sufficiently consistent basis for a defensible cross-platform calculation. The present review can therefore identify the economic mechanism by which multifunctionality may improve utilisation and distribute capital cost across tasks, but a numerical payback or ROI estimate would require a dedicated techno-economic study using harmonised assumptions and field-derived operational data.

4.3. Future Research Directions

The reviewed studies indicate that a multifunctional raspberry robotic platform should be based on a shared mobile, computing, navigation, communication, and robotic-arm infrastructure, while perception models, sensors, control parameters, and crop-contact tools remain task-specific [13,14,78]. This architecture is particularly relevant because harvesting, pruning, and targeted application impose substantially different requirements. Harvesting primarily requires reliable fruit localisation and gentle manipulation [23,63–77,79,80,84], whereas pruning additionally requires interpretation of cane structure, selection of appropriate cutting points, and collision-free access [5,31,32,36,40–44]. Targeted application requires accurate target localisation together with verification of treatment delivery and efficacy [14,59–62].

Future work should therefore focus first on validating these task-specific modules for raspberry and subsequently integrating them through common mechanical, electrical, and software interfaces. The resulting platform should then be evaluated under common field protocols across cultivars, phenological stages, seasons, and production environments, including perception and localisation accuracy, task success, cycle time, crop damage or off-target effects, reliability, and energy use. Such field data would also provide the basis for a meaningful economic assessment of multifunctional operation.

5. Conclusions

This review examined robotic-arm applications across the raspberry production cycle, with particular emphasis on cane management, crop monitoring and yield estimation,

targeted spraying, harvesting, end-effector technologies, and multifunctional robotic platforms. The aim was to assess the current state of these technologies and their potential for broader seasonal use in raspberry production.

The reviewed literature shows that raspberry-specific robotic development remains concentrated mainly on harvesting, while other operations are represented primarily by perception-focused studies or robotic solutions developed for related horticultural crops. At the same time, substantial progress has been made in raspberry-specific fruit detection, maturity assessment, and crop monitoring. Robotic solutions for pruning and targeted spraying remain scarce, and no raspberry-specific robotic platform was identified that had been demonstrated across multiple operations of the production cycle. However, several enabling technologies relevant to such a platform have already been demonstrated in raspberry and related horticultural crops, including modular robotic architectures, shared sensing and control systems, and interchangeable end-effectors.

Future research could therefore focus on integrating these technologies into a common multifunctional platform and validating it under realistic raspberry production conditions. Using the same robotic platform for multiple operations throughout the production cycle may increase platform utilisation, improve cost-effectiveness, and support the practical adoption of robotic systems in raspberry production.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

2D	Two-Dimensional
3D	Three-Dimensional
3P + 3R	3 Prismatic + 3 Revolute joints
4WD	Four-Wheel Drive
ABS	Air-Blast Sprayer
AI	Artificial Intelligence
ALNS	Adaptive Large Neighborhood Search
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
AP	Average Precision
API	Application Programming Interface
BLE	Bluetooth Low Energy
CAN/CAN-BUS	Controller Area Network/Controller Area Network Bus

CG	Context Guided
CHT	Circular Hough Transform
CNN	Convolutional Neural Network
CPCA	Channel Prior Convolutional Attention
CROPS	Clever Robots for Crops
CV	Computer Vision
DA	Diels–Alder
DH	Denavit–Hartenberg
DL	Deep Learning
DoF	Degrees of Freedom
DWR	Dilation-Wise Residual
EKF	Extended Kalman Filter
EST	Expansive Space Trees
FastDTW	Fast Dynamic Time Warping
FN	False Negative
FP	False Positive
fps	Frames Per Second
GFLOPs	Giga Floating-Point Operations
GIoU	Generalized Intersection over Union
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GUI	Graphical User Interface
HCSA	Halo attention with Channel and Spatial Attention modules
HSA	HSV Self-Adaption
HSV	Hue, Saturation, Value
ICP	Iterative Closest Point
IGA	Internal Grant Agency
IK	Inverse Kinematics
IMU	Inertial Measurement Unit
IoU	Intersection over Union
KPIECE	Kinodynamic Planning by Interior–Exterior Cell Exploration
LiDAR	Light Detection and Ranging
LITRP	Laboratory of Technological Research in Pattern Recognition
LOD	Logarithm of Odds
MA	Mechanical Advantage
mAP	Mean Average Precision
ML	Machine Learning
MPC	Model Predictive Control
MQTT	Message Queuing Telemetry Transport
MST	Minimum Spanning Tree
N/A	Not Applicable
N/R	Not Reported
NDRE	Normalized Difference Red Edge Index
NIR	Near-Infrared
NMS	Non-Maximum Suppression
NSGA-II	Non-dominated Sorting Genetic Algorithm II
NTP	Network Time Protocol
OMPL	Open Motion Planning Library
PCA	Principal Component Analysis
PID	Proportional–Integral–Derivative
PPO	Proximal Policy Optimization
QP	Quadratic Programming
QTL	Quantitative Trait Locus
R-CNN	Region-based Convolutional Neural Network

RE	Red Edge
REML	Restricted Maximum Likelihood
REST	Representational State Transfer
RGB	Red, Green, Blue
RGB-D	Red, Green, Blue + Depth
RMS	Root Mean Square
RMSE	Root Mean Square Error
ROI	Return on Investment
ROS	Robot Operating System
RRT	Rapidly exploring Random Tree
RT-DETR	Real-Time Detection Transformer
RTK	Real-Time Kinematic
RTK-GNSS	Real-Time Kinematic Global Navigation Satellite System
RTK-GPS	Real-Time Kinematic Global Positioning System
SDGD-YOLO	StarNet-DySample-GIoU-Distillation YOLO
Soft-NMS	Soft Non-Maximum Suppression
SVD	Singular Value Decomposition
SVM	Support Vector Machine
SWIR	Short-Wave Infrared
TCP/IP	Transmission Control Protocol/Internet Protocol
TF	Transform Framework
ToF	Time of Flight
TP	True Positive
TPE	Total Pruning Efficiency
UAV	Unmanned Aerial Vehicle
UDP	User Datagram Protocol
UGV	Unmanned Ground Vehicle
USB	Universal Serial Bus
VIS	Visible
VNIR	Visible and Near-Infrared
WIoU/WIoUv2	Wise Intersection over Union/Wise-IoU version 2
YOLO	You Only Look Once

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