

Review

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Review

Ground Mobile Robots for High-Throughput Plant Phenotyping: Perception, Decision, and Action

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Abstract

High-throughput plant phenotyping is increasingly constrained by the mismatch between the demand for field-relevant, fine-grained phenotypic data and the limited capability of conventional observation platforms under complex agricultural conditions. In this context, mobile phenotyping systems, particularly ground robots, are emerging as a key technological pathway for bridging macro-scale monitoring and organ-level trait analysis. This review examines the development of mobile phenotyping platforms for high-throughput plant phenotyping, with emphasis on the evolving role of ground robots in field-based sensing, decision-making, and active interaction. We first compare the functional characteristics of unmanned aerial vehicles and unmanned ground vehicles and discuss their complementarity in multiscale phenotypic data acquisition. We then summarize recent advances in the core technical framework of mobile phenotyping robots, including multimodal perception, localization and mapping, motion planning, deep-learning-based phenotypic analysis, active observation, robotic intervention, and edge deployment. Major challenges are further discussed, particularly those related to environmental generalization, data annotation, standardization, reproducibility, and long-term field reliability. Finally, future directions are outlined from the perspectives of air-ground collaboration, multi-robot systems, foundation models, and embodied intelligence. This review highlights ground robots as a central carrier for advancing mobile phenotyping toward autonomous, fine-grained, and field-deployable systems.

Keywords: high-throughput plant phenotyping; unmanned ground vehicles; mobile robotics; multimodal sensing; field phenotyping; precision agriculture; deep learning

1. Introduction

Global agricultural production is under growing pressure from two converging forces: steadily rising food demand and escalating climate risk [1,2]. United Nations projections indicate that the global population will reach approximately 9.7 to 10 billion around 2050, sustaining long-term growth in demand for food and feed [1]. At the same time, the Sixth Assessment Report of the Intergovernmental Panel on Climate Change warns that climate warming and the increasing frequency of extreme weather events have already become tangible threats to global food security and will further intensify the vulnerability of agricultural systems in the future [2,3]. Against this backdrop, improving resource-use efficiency and system resilience through crop breeding has become a key technological pathway for supporting sustainable agricultural development [4–7].

Over the past two decades, rapid advances in genomics and high-throughput sequencing/genotyping technologies have substantially lowered the cost and technical barriers associated with acquiring genotypic information, making large-scale characterization of genetic variation increasingly routine [8,9]. In contrast, the efficient, standardized, and reproducible acquisition of phenotypic data under real field conditions has progressed much more slowly, creating a major bottleneck for modern

breeding. This gap is particularly critical because the dissection of complex agronomic traits, such as yield, stress resistance, and resource-use efficiency, depends heavily on real phenotypic evidence under genotype-by-environment ($G \times E$) and genotype-by-environment-by-management ($G \times E \times M$) interactions. As a result, the quality, throughput, and environmental representativeness of phenotypic data directly affect the analytical power and practical transferability of genome-wide association studies (GWAS), quantitative trait locus (QTL) mapping, and genomic selection [10–12]. In this context, together with the rapid development of artificial intelligence [13–16], High-Throughput Plant Phenotyping (HTPP) has emerged as a key technological framework for linking genomic information with field-relevant phenotypic evidence. Its central aim is to quantitatively characterize plant morphology and physiological processes across large populations, diverse environments, and multiple time points, thereby supporting both breeding selection and precision field management [1,17,18].

Although existing HTPP technologies have, to some extent, alleviated the low efficiency and inconsistency associated with traditional manual measurements, their applicability in complex field environments remains limited. Automated greenhouse systems and conveyor-based platforms in controlled environments can provide highly consistent imaging conditions and standardized data acquisition, but they cannot faithfully reproduce the fluctuating illumination, wind disturbance, terrain variation, and population heterogeneity of open-field settings. Consequently, the extent to which their phenotypic outputs can be extrapolated to real agricultural environments remains constrained [4]. By contrast, Unmanned Aerial Vehicles (UAVs), with their rapid response, broad coverage, flexible deployment, and relatively low cost [19,20], have become important platforms for temporal remote sensing in breeding trials [21,22]. Equipped with RGB, multispectral, and thermal infrared sensors, UAVs can efficiently capture canopy-scale traits related to crop growth, stress responses, and certain yield-associated indicators [23–25]. However, as high-throughput phenotyping shifts from simply acquiring data to acquiring data that are sufficiently detailed and directly actionable for decision-making, the central challenge is no longer data collection per se, but rather the mismatch among observation precision, system robustness, and end-to-end automation under complex field conditions [3,26].

More specifically, current mobile phenotyping systems still face several major constraints. First, because UAVs primarily rely on top-view or oblique-view observations of the canopy, they are highly susceptible to occlusion in dense plantings or tall crops, which limits their ability to stably measure lower-canopy and organ-level traits. As a result, traits such as stem architecture, ear or fruit morphology, lower-leaf posture, and early concealed symptoms of pests and diseases are difficult to capture reliably [21,24,27]. In contrast, although Unmanned Ground Vehicles (UGVs) can acquire high-resolution, close-range, and multi-view data, they generally lag behind UAVs in operating speed, area coverage efficiency, and adaptability to complex terrain, making it difficult for them to independently satisfy the throughput and timeliness requirements of large-scale breeding trials [28]. Second, traditional cart-based platforms and manual close-range sampling can enter crop rows and collect data at high spatial resolution, but they remain labor-intensive, low-throughput, and highly dependent on operator experience and workflow consistency, limiting their suitability for large-scale standardized field phenotyping [1,26]. Third, many current phenotypic analysis methods and system pipelines are still validated primarily on offline datasets, and their engineering readiness for real field deployment remains insufficient. Under challenging conditions such as abrupt illumination changes, wind-induced leaf motion, muddy terrain, weed interference, and long-term unattended operation, substantial weaknesses persist in perception robustness, closed-loop data transmission and processing, online decision-making, and long-term operational stability. These limitations have become major barriers to the integrated deployment of algorithms, platforms, and practical applications [26,29–31].

Against this background, and in pursuit of precise phenotypic analysis that is multi-scale, comprehensive, and deployable in practice, research is gradually moving away from single-platform observation toward a mobile phenotyping paradigm centered on ground robots and complemented by air–ground collaboration [30,32]. Compared with UAVs, UGVs can operate within crop rows

and beneath the canopy while carrying heavier and more complex sensor suites, such as multi-view imaging systems, LiDAR, and close-range spectrometers. They are therefore better suited for organ-level structural trait measurement, fine-grained observation under occlusion, and three-dimensional reconstruction [33,34]. Existing studies have already demonstrated the significant potential of autonomous field robots for high-throughput, high-resolution 3D phenotyping, while also revealing the navigation, perception, and system integration constraints associated with deployment in real agricultural environments. Together, these findings suggest that combining close-range 3D sensing with autonomous mobility is a promising direction for overcoming occlusion and enabling the quantification of complex structural traits [29,35]. At the same time, air-ground collaboration (UAV-UGV) offers a scalable workflow that balances coverage efficiency with information density: UAVs perform large-area scanning, anomaly detection, and task guidance, while UGVs conduct targeted close-range measurements and fine-grained information completion, thereby achieving a better balance between overall throughput and local precision [32,36,37].

In light of these developments, this review goes beyond a simple catalog of mobile platforms and sensor configurations and instead reframes high-throughput plant phenotyping, from a robotic systems perspective, as a closed-loop engineering problem of perception, decision-making, and action in complex field environments. To this end, we first compare the functional roles and complementarities of UAVs, ground robots, and their collaborative modes in multi-scale phenotypic data acquisition. Building on this, we focus primarily on ground mobile robots and systematically review recent advances in the core technical framework spanning perception, decision-making, and action, with particular emphasis on multimodal sensing and autonomous localization, phenotype analysis driven by deep learning and generative artificial intelligence, and key enabling capabilities such as chassis control and active robotic manipulation. We then discuss edge computing, model lightweighting, and the practical challenges of field deployment under complex environmental conditions. Finally, we examine major bottlenecks, including environmental generalization, the scarcity of high-quality annotated data, and the lack of standardized benchmarks, and we outline future directions in multi-robot collaboration, standard system development, and embodied intelligence for agriculture.

2. Mobile Phenotyping Platforms

With the rapid development of high-throughput plant phenotyping, traditional static observation facilities are increasingly unable to meet the demand for high-frequency, multidimensional, and multiscale monitoring of crop growth under open-field conditions. Compared with fixed platforms, mobile phenotyping systems can maintain broad spatiotemporal coverage while flexibly integrating diverse sensor types, thereby substantially improving the efficiency, resolution, and environmental adaptability of field phenotypic data acquisition. At present, the principal mobile platforms used for field-based high-throughput phenotyping are Unmanned Aerial Vehicles (UAVs) (Figure 1(a,b)) and Unmanned Ground Vehicles (UGVs) (Figure 1(c,d)). The former are particularly effective for rapid, large-area, non-contact observation, whereas the latter are better suited for high-resolution, fine-grained phenotyping in near-canopy and under-canopy environments. Figure 1 illustrates representative field applications of these two platform types. Notably, although UAVs play an important role in field phenotyping, their main strengths lie in large-scale coverage and rapid canopy-level observation. By contrast, for the close-range sensing, autonomous navigation, environment interaction, and intervention-oriented capabilities emphasized in later sections, UGVs serve as the more direct technical carrier. Accordingly, this section briefly reviews UAV-based platforms, then focuses on the configurations, operational modes, and engineering constraints of UGVs, and finally discusses the system-level potential of UAV-UGV collaboration in high-throughput plant phenotyping.

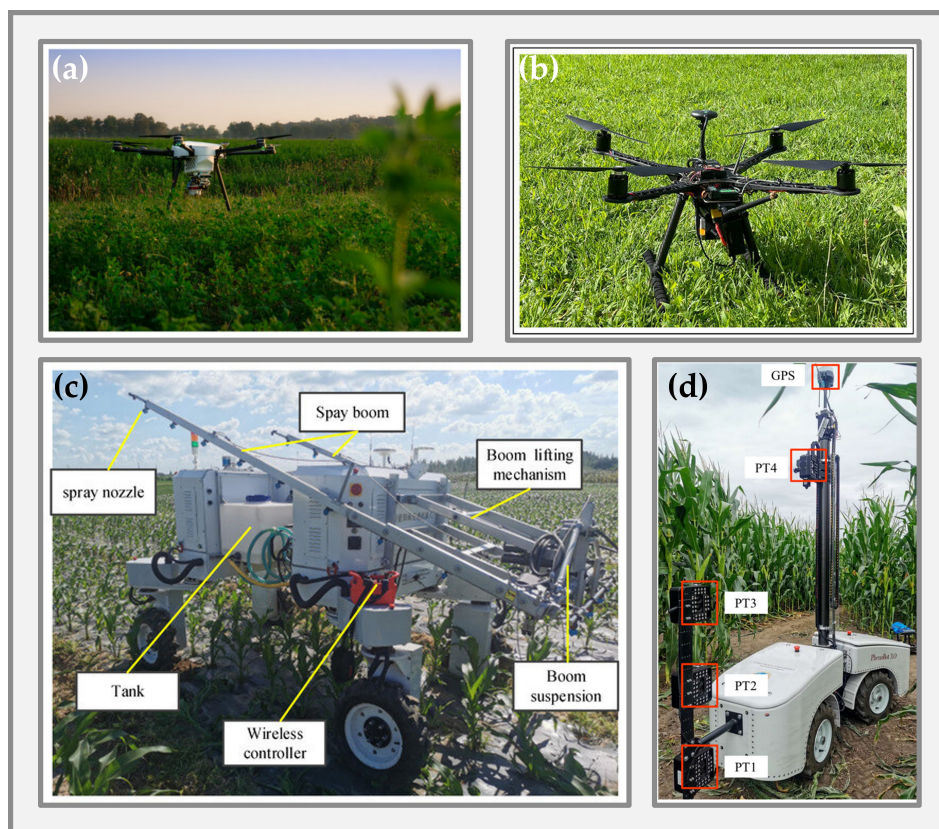


Figure 1. Representative examples of mobile plant phenotyping platforms under field conditions: (a) [38] and (b) [39] are UAV platforms; (c) [40] and (d) [41] are UGV platforms.

2.1. Unmanned Aerial Vehicles (UAVs)

As non-contact remote sensing platforms, UAVs have become one of the most representative mobile solutions for field crop phenotyping because of their rapid deployment, broad coverage, and ability to carry multiple sensing payloads. Compared with manual ground surveys, UAVs can acquire data over large plots or even farm-scale areas within a short time, effectively overcoming the spatial and temporal limitations of conventional approaches [8]. They are therefore particularly well suited to periodic monitoring at key growth stages and to the rapid extraction of macro-scale phenotypic traits such as canopy structure, population vigor, and stress response [8,42].

From the standpoint of platform configuration, UAVs commonly used in agricultural phenotyping can be broadly classified into multirotor, fixed-wing, and hybrid types [43,44]. Multirotor UAVs can take off and land vertically and hover in place, allowing flexible operation in spatially constrained field environments and enabling low-speed or stationary image acquisition with high overlap, which is advantageous for improving the geometric accuracy of orthomosaics and 3D reconstruction [45]. However, these platforms are typically constrained by battery capacity, resulting in relatively short flight duration and limited suitability for long-endurance or ultra-large-area missions [37]. By contrast, fixed-wing UAVs rely on aerodynamic lift during cruise and therefore provide greater flight range and coverage, making them more appropriate for continuous farm-scale monitoring and regional crop growth assessment [46]. In recent years, hybrid UAVs that combine the takeoff flexibility of multirotor systems with the cruise efficiency of fixed-wing platforms have attracted increasing attention and are regarded as a promising option for large-scale field phenotyping [47].

The phenotyping capability of UAVs depends to a large extent on the types of sensors they carry. RGB cameras, when combined with photogrammetry and Structure from Motion (SfM) algorithms [48], can reconstruct 3D canopy point clouds from multi-view 2D imagery and support the extraction of phenotypic traits such as plant height, canopy cover, and micro-topography. Previous studies have shown that plant height estimated from UAV-SfM is highly consistent with manual measurements [49].

Multispectral and hyperspectral imaging can capture key spectral bands such as the red-edge and near-infrared (NIR), enabling the calculation of vegetation indices such as NDVI and NDRE to reflect leaf nitrogen status, chlorophyll content, and photosynthesis-related characteristics [50–52]. For example, Shao et al. [53] combined UAV multispectral and thermal infrared imagery with machine learning to achieve high-accuracy estimation of aboveground biomass (AGB) in maize. In addition, compared with passive optical imaging, LiDAR provides stronger canopy penetration and can effectively alleviate ground-point loss and the resulting bias in plant height estimation under dense canopy conditions [54].

Despite the substantial gains in throughput offered by UAVs for large-area field phenotyping, they are inherently constrained by both their observation geometry and their task capabilities. First, because UAVs primarily rely on top-view or oblique-view observation, they are highly susceptible to canopy occlusion and therefore limited in their ability to stably capture organ-level or under-canopy traits such as stem structure, lower-leaf posture, ear or fruit morphology, and concealed pest or disease symptoms. Second, their payload capacity, endurance, and onboard computing resources are all constrained by platform size and power systems, which in turn limit their use in continuous close-range observation, complex environmental interaction, and active intervention tasks. Overall, UAVs are better suited to rapid scanning and macro-scale perception over large areas than to high-precision, near-canopy, and long-duration continuous observation when used alone.

2.2. Unmanned Ground Vehicles

Unlike UAVs, which primarily provide canopy-scale top-view information, ground robots can enter crop rows or move beneath the canopy and acquire high-fidelity phenotypic data from side-view, horizontal-view, or even upward-view perspectives that are closer to target organs [55,56]. As a result, UGVs possess inherent advantages in organ-level trait extraction, 3D structural reconstruction, perception under occlusion, and continuous close-range monitoring, making them the core platform type with greater engineering extensibility in current mobile phenotyping systems [26,57,58]. In terms of mechanical configuration and typical application scenarios, agricultural phenotyping UGVs can generally be categorized into high-clearance cross-row platforms (Figure 2(a)), compact inter-row platforms (Figure 2(b)), and modular research platforms (Figure 2(c)) [26,59–62]. These different configurations emphasize different trade-offs in traversability, payload capacity, near-canopy sensing mode, and system integration flexibility, together forming a UGV platform spectrum for different crop types, field conditions, and research objectives.

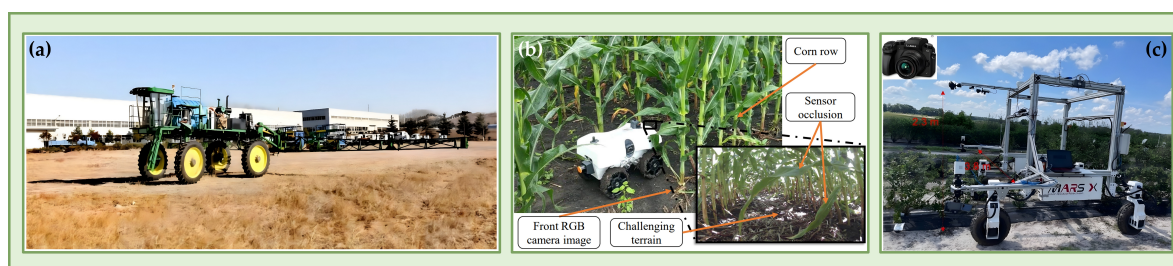


Figure 2. Three typical unmanned ground vehicles for agricultural scenarios. (a) High-clearance platform [59]; (b) compact inter-row platform [60]; (c) modular research platform [61,62].

High-clearance cross-row platforms are typically built on tractor-based or specially designed high-mobility chassis and are well suited to phenotyping tall crops such as maize and sorghum. These platforms provide large ground clearance and strong payload capacity, allowing simultaneous integration of multispectral cameras, near-infrared cameras, LiDAR, and other sensors for non-destructive measurement of multiple agronomic traits, including canopy structure, biomass, water status, and lodging characteristics [63]. For example, the BreedVision platform uses a multi-sensor configuration to acquire crop water content, lodging rate, tiller density, biomass, and other traits directly in the field [64]. The main advantages of this platform type are high payload redundancy and strong system

stability, which make it suitable for synchronized acquisition of multi-source sensor data, although its large physical size generally reduces maneuverability and flexibility.

Compact inter-row platforms place greater emphasis on traversability in narrow spaces and close-range observation. They can move steadily at low speed within crop rows and approach target organs such as leaves, stems, and fruits from the side or from below the canopy, thereby effectively mitigating the occlusion problems associated with top-view observation [65]. TerraSentia is a representative example of such a compact autonomous ground platform [66]. Equipped with multiple RGB cameras and LiDAR, it can perform high-precision scanning within maize rows and extract latent phenotypic features using deep learning methods [67], supporting plant structure modeling and biomass distribution estimation. This side-view or under-canopy observation mode is especially advantageous for capturing fine-scale phenotypic information, such as leaf number, stem diameter, inter-plant structural variation, and localized disease symptoms, that is difficult to resolve robustly from aerial views [68,69]. Compared with high-clearance platforms, inter-row UGVs are better adapted to organ-level data acquisition and occlusion-rich scenarios and are more closely aligned with the later development of closed-loop perception–decision–action systems.

Modular research platforms are primarily intended for algorithm validation, system integration, and functional extension. Representative examples include Clearpath Robotics' Husky and Saga Robotics' Thorvald [70,71]. These platforms typically provide open mechanical and electrical interfaces and are compatible with mainstream robotic software frameworks such as ROS, enabling rapid integration of cameras, LiDAR, robotic arms, and spectral sensors for experimental validation of field navigation, visual recognition, and phenotype extraction methods [72]. Their key strengths lie in high system reliability, strong extensibility, and good experimental reproducibility, which make them widely useful for comparing the effects of different sensor configurations, algorithmic frameworks, and control strategies on phenotyping quality and operational performance [73,74]. Although they may not offer optimal traversability or efficiency for highly specialized agricultural tasks, they are highly valuable for supporting rapid method development and prototyping.

Overall, UGVs substantially expand both the depth and dimensionality of field phenotypic data acquisition through their close-range, multi-view, and high-payload operational characteristics. In particular, for tasks involving organ-level phenotyping, under-canopy structural analysis, long-term continuous monitoring, and the integration of sensing with action, UGVs exhibit stronger engineering suitability than UAVs. From the perspective of advancing high-throughput plant phenotyping toward autonomy, fine-grained observation, and closed-loop operation, UGVs are not only an important component of mobile phenotyping platforms but also the principal carrier of the core technical framework discussed in the following sections.

2.3. Comparative Advantages and Limitations of UAVs and UGVs

From the standpoint of phenotyping requirements, UAVs and UGVs should not be viewed as simple substitutes for one another. Rather, they exhibit clear functional differentiation in terms of spatial scale, observation depth, operational throughput, and environmental interaction. The main strengths of UAVs lie in their high mobility, broad coverage, and relatively simple deployment, which make them suitable for rapid large-area scanning and for extracting macro-scale phenotypic indicators such as canopy height, coverage, population vigor, and thermal stress [45,75]. However, their predominantly top-view or oblique-view observation geometry inevitably introduces occlusion-related limitations. This is particularly problematic in dense, tall crops such as maize and sorghum after canopy closure, where upper leaves often block the middle and lower organs, making it difficult for UAVs to stably capture key agronomic traits such as stem diameter, basal disease symptoms, and ear or fruit morphology [76–79]. Moreover, although UAVs substantially improve acquisition throughput, their ability to resolve small lesions, early pest infestation, and fine close-range structural details remains limited by flight altitude, endurance, and payload constraints [37,76,80].

In contrast, UGVs can operate much closer to target plants and collect high-resolution data from downward, side, and horizontal viewpoints. Their stronger payload capacity also allows integration

of multimodal sensor systems, enabling richer characterization of organ-level and under-canopy traits [18]. In addition, UGVs typically support longer continuous operating times, making them more suitable for continuous or semi-continuous monitoring of localized areas and for the integration of subsequent active intervention tasks. Nevertheless, UGVs also have important limitations. Because they move more slowly and cover less area per day, and because they must address inter-row path planning, autonomous localization, obstacle avoidance, and traversal over complex terrain, their deployment is usually more complicated than that of UAVs. In addition, muddy surfaces, slope variation, and dense canopy obstruction can further affect their motion stability and navigation accuracy [18,37]. Accordingly, the difference between UAVs and UGVs is not merely a distinction between aerial and ground platforms, but rather a distinction between two complementary yet difficult-to-unify task demands in high-throughput plant phenotyping: high-throughput observation for broad-area coverage and rapid screening, and high-information-density observation for fine structural analysis and continuous close-range monitoring. A single platform rarely satisfies both requirements simultaneously. For this reason, UAVs are more appropriate for global perception and regional screening, whereas UGVs are more appropriate as the core carrier for near-canopy precision observation, complex environmental interaction, and closed-loop operation. Table 1 summarizes the key characteristics of the two platform types.

Table 1. Comparison of key characteristics of UAVs and UGVs in high-throughput plant phenotyping.

Characteristic	UAV	UGV
Typical operating mode	Aerial imaging, primarily from top-view or oblique-view perspectives	Autonomous ground locomotion, primarily from horizontal, side, or upward-view perspectives
Typical coverage scale	Large, from plot to farm scale [75]	Small to medium, typically localized plots or inter-row areas [37]
Main observation targets	Population-scale traits such as overall canopy structure, coverage, plant height, and thermal stress	Organ-level and under-canopy traits such as stems, leaves, ears, and fruits
Observation geometry	Primarily top-view, strongly affected by canopy occlusion	Close-range multi-view observation, effective for alleviating occlusion
Sensor payload capacity	Relatively limited, typically lightweight cameras or spectral sensors	Stronger, enabling integration of multiple cameras, LiDAR, spectrometers, robotic arms, and related systems
Spatial resolution and information depth	Can achieve high spatial resolution, but mainly reflects canopy surface information	Closer to the target, enabling high-fidelity organ-level and structural information acquisition
Endurance / continuous operation	Strongly constrained by energy, with relatively short single-mission duration	Can operate continuously for several hours, suitable for continuous or semi-continuous monitoring
Operational efficiency	Fast movement, suitable for rapid screening and global scanning	Slower operation, but stronger for precision measurement
Deployment complexity	Relatively low, mainly dependent on flight planning and remote sensing mission organization	Relatively high, requiring navigation, obstacle avoidance, path planning, and terrain adaptation
Main advantages	High throughput, broad coverage, rapid acquisition of canopy-scale information	High precision, near-canopy, multi-view sensing, well suited to fine-grained observation and active intervention
Main limitations	Difficulty in stably capturing under-canopy and organ-level traits; constrained by endurance and payload [37,76,80]	Limited coverage; high requirements for terrain adaptability and autonomous navigation [18,37]

2.4. UAV–UGV Collaboration

Given the strong complementarity of UAVs and UGVs in terms of coverage efficiency and observation precision, air–ground collaboration has gradually emerged as an important direction in high-throughput plant phenotyping [81]. Its core idea is not simply to combine two platform types, but to construct a task-layered workflow of “global scanning–local precision measurement” through information transfer and functional division (Figure 3). In this framework, UAVs perform rapid large-

area scouting, canopy information extraction, and the identification of potentially anomalous regions, while UGVs use aerial prior information to conduct targeted navigation, close-range observation, and even active sampling. In this way, both throughput and data granularity can be balanced under limited time and resource constraints [18,82]. Existing studies have provided initial evidence of the feasibility of this paradigm. For example, Yue et al. [83] proposed the deep learning framework MSRNet based on coordinated UAV–UGV multi-view imaging, integrating UAV top-view canopy imagery with UGV side-view ear imagery, and achieved an overall accuracy of 84.5% in maize developmental stage recognition, representing an improvement of 3.8%–13.6% over single-view models. Notably, Tan et al. [84] introduced transfer learning by fine-tuning an object detection model pre-trained on UGV imagery using UAV imagery, and, together with the Segment Anything Model (SAM), proposed an optimized DM-Count model that successfully achieved cotton boll mapping. Similarly, Petti et al. [85] incorporated transfer learning with both UAV and UGV imagery to accomplish phenotyping tasks for cotton flowers, thereby advancing breeding research. These studies indicate that cross-platform multi-view information fusion can improve phenotypic recognition accuracy while also mitigating the information loss associated with single-view observation.

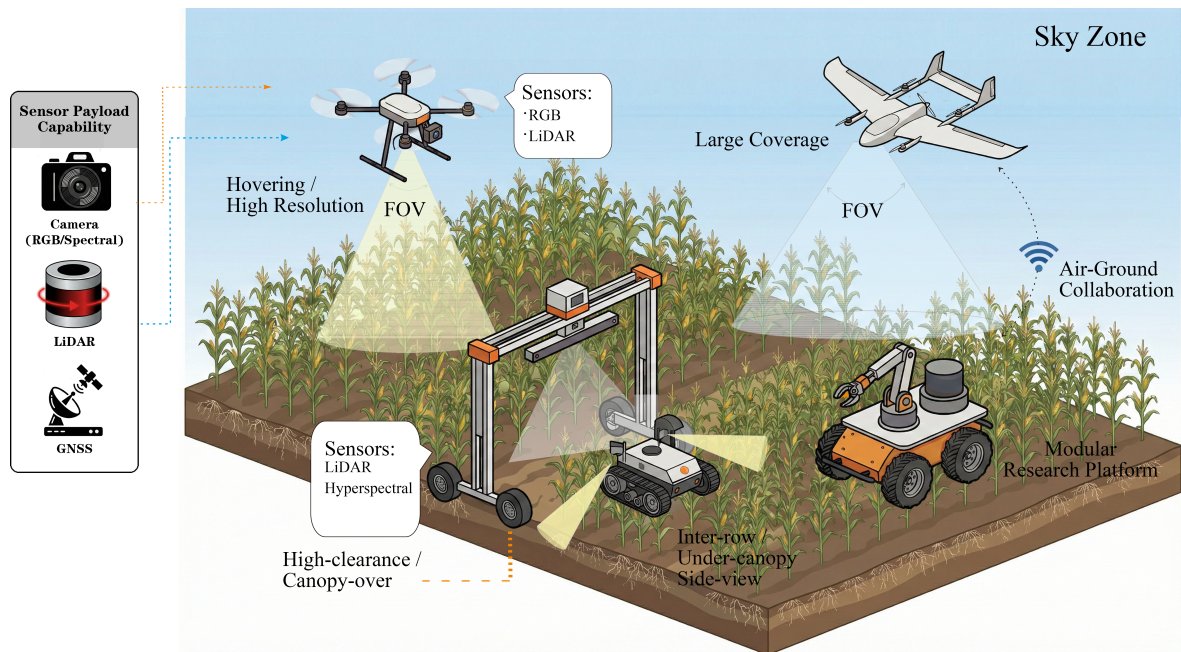


Figure 3. Schematic illustration of the collaborative air–ground framework for high-throughput plant phenotyping. **Note:** This figure shows the functional division and coordination between aerial and ground mobile platforms in complex field environments. The aerial layer includes multirotor UAVs for high-resolution hovering observation and fixed-wing platforms for rapid large-area coverage, both of which primarily support broad canopy-scale perception. The ground layer includes high-clearance platforms, inter-row platforms, and modular research platforms, which are mainly used for fine-grained acquisition of near-canopy, under-canopy, and organ-level phenotypic information. The dashed arrows indicate the task transition from aerial global scanning to ground-based targeted precision measurement, while the legend on the left summarizes the typical sensor payloads that can be integrated on different platforms, illustrating the multiscale collaborative strategy of “broad-area scanning–local precision measurement” in high-throughput plant phenotyping.

Despite its promise, air–ground collaboration still faces several system-level challenges. First, at the perception level, data collected by different platforms must be aligned spatiotemporally within a unified coordinate system and semantically reconciled to ensure spatial consistency and interpretability in downstream information fusion [86]. Second, at the decision level, efficient scheduling and task planning mechanisms are required to ensure that UAVs and UGVs can divide responsibilities appropriately, compensate dynamically for each other, and avoid resource conflicts during collaborative operation [55]. Third, at the execution level, stable inter-platform communication, task allocation,

and state synchronization are all critical to overall system efficiency [87]. Looking ahead, developments in multi-UAV formations, heterogeneous robot teams, 5G communication, and distributed control are expected to further improve continuous sensing and dynamic management over large-scale agricultural fields [88,89]. Nevertheless, from the perspective of the technical focus of this review, air-ground collaboration is better understood as an extensible framework for large-scale phenotyping systems, whereas the core platform that truly carries the closed-loop capabilities of close-range sensing, autonomous decision-making, and environment interaction remains the ground robot.

3. Core Technology: Perception, Decision, and Action

As smart agriculture moves beyond proof-of-concept toward large-scale deployment in real-world settings, high-throughput plant phenotyping is undergoing a fundamental shift from static observation platforms to mobile robotic systems. Conventional phenotyping platforms have largely relied either on automated facilities in controlled environments or on relatively simple remote sensing approaches. While these systems offer advantages in standardization and throughput, they often struggle to simultaneously achieve environmental adaptability, sensing precision, and sustained operation under complex field conditions. By contrast, modern mobile phenotyping systems designed for open-field environments must do more than acquire plant images or point clouds; they must continuously perform environmental understanding, autonomous mobility, target interpretation, and physical interaction in unstructured settings. Accordingly, the central challenge in high-throughput plant phenotyping is no longer the performance improvement of an individual sensor or algorithm, but the construction of an autonomous closed-loop robotic framework integrating perception, decision-making, and action.

At the system level, this closed loop comprises at least four tightly coupled components. First, the perception layer must simultaneously interpret the environment and plant targets: the former provides geometric and semantic information for localization, mapping, and navigation, while the latter supplies high-spatiotemporal-resolution data for analyzing plant morphology, physiology, and pathology. Second, the decision layer integrates information at two levels, motion planning and phenotypic understanding, so that the robot can operate safely and efficiently in complex field environments while converting multisource observations into interpretable and quantifiable phenotypic traits. Third, the action layer reflects the fundamental advantage of robots over conventional remote sensing platforms: beyond simply reaching and seeing a target, the system can actively improve observation conditions and expand measurable trait boundaries through chassis posture adjustment, viewpoint adaptation, robotic-arm-assisted supplementary imaging, and contact-based operations. Finally, the deployment layer determines whether these capabilities can be translated into field practice, subject to engineering constraints such as edge inference, thermal management, communication, and energy supply. Following this logic, the remainder of this section reviews recent advances in mobile phenotyping robots from the perspectives of perception, decision-making, action, and deployment.

3.1. Perception: From Multimodal Observation to Integrated Localization-Aware Sensing

The perception system is the information entry point of a mobile phenotyping robot, and its role now extends far beyond conventional image acquisition. In real field environments, it must simultaneously fulfill two tasks: environmental perception for the robot itself, which supports localization, mapping, navigation, and obstacle understanding [90–93], and trait perception for plant targets, which enables analysis of crop morphology, physiological status, and pathological response [94–97]. This dual requirement means that mobile phenotyping systems cannot rely on a single sensing modality, but instead must improve robustness and information density through the coordinated use of multimodal sensing, 3D reconstruction, and semantic understanding. Figure 4 summarizes representative sensing modalities commonly used in mobile phenotyping, including RGB/RGB-SfM [98], LiDAR [99], thermal infrared imaging [100], and hyperspectral imaging [101], together with their typical phenotyping tasks.

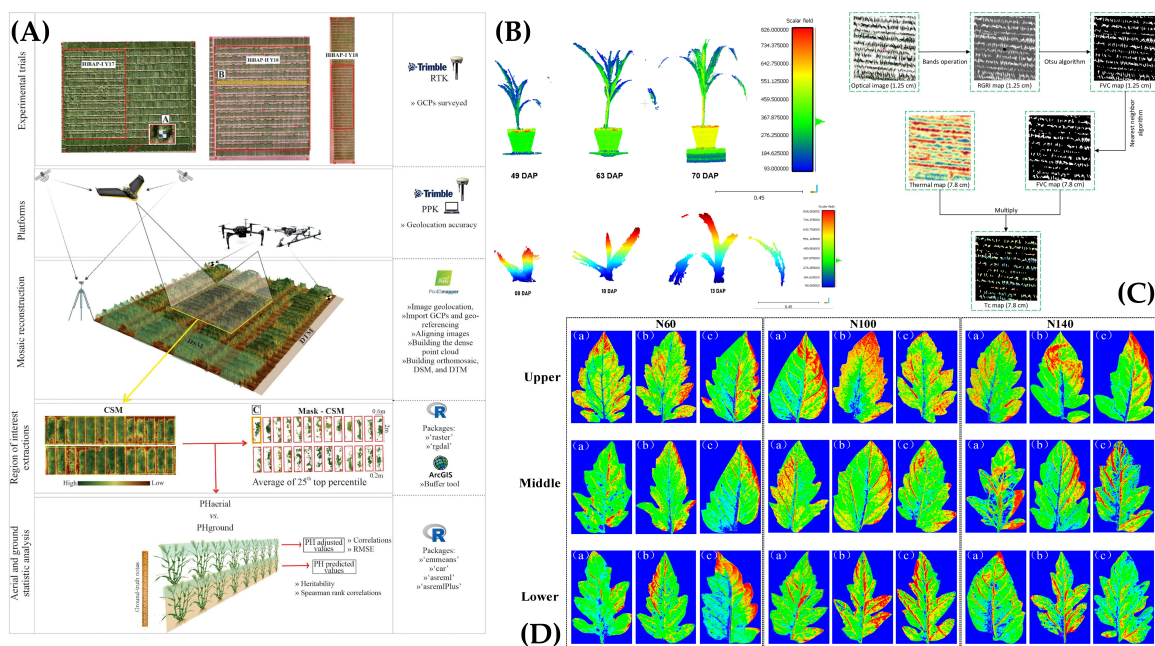


Figure 4. Common sensing modalities used in mobile phenotyping platforms and their corresponding trait analysis tasks. **(A)** RGB/RGB-SfM: used for canopy morphology characterization and 3D crop surface reconstruction, supporting extraction of canopy coverage, organ counts, and plant height [98]; **(B)** LiDAR: provides penetrative 3D point clouds for canopy structure, organ geometry, and plant spatial architecture analysis [99]; **(C)** thermal infrared imaging: characterizes transpiration, stomatal conductance, and water stress through canopy temperature distribution [100]; **(D)** hyperspectral imaging: enables visualization of biochemical indicators such as leaf nitrogen and chlorophyll based on spectral responses at different wavelengths [101].

From the perspective of trait perception, visible-light sensing remains the most widely used foundational modality because of its high spatial resolution, low cost, and ease of deployment. Two-dimensional RGB imagery serves as a primary data source for tasks such as leaf area index estimation, coverage analysis, crop density assessment, maturity detection, and organ counting [102–104]. Through color-space transformations such as HSV, it can also support crop–soil background separation and the identification of macroscopic visual symptoms such as nitrogen-deficiency chlorosis and necrotic lesions [95]. Furthermore, when combined with Structure from Motion (SfM) and Multi-View Stereo (MVS), sequential RGB imagery can reconstruct 3D canopy point clouds, enabling estimation of structural traits such as plant height, biomass, and canopy volume [105]. In addition, some studies have used segmentation algorithms to extract crop shape directly from 2D RGB images [106]. Previous work has shown that low-cost vision-based reconstruction can achieve accuracy comparable to LiDAR for tasks such as plant height estimation. For instance, Madec et al. [107] demonstrated that UAV-SfM can achieve centimeter-level accuracy comparable to LiDAR in estimating plant height and row width, while Fujiwara et al. [108] reported that low-cost vision-based reconstruction was not inferior to RTK-based high-cost solutions for predicting maize height across growth stages. Nevertheless, as a passive imaging modality, RGB sensing is highly sensitive to illumination changes, shadow occlusion, and canopy closure, and is particularly limited in reliably capturing internal structures within dense canopies [109].

Compared with RGB, LiDAR provides a more stable physical basis for 3D structural analysis. By actively emitting laser pulses and measuring their time of flight (ToF), LiDAR acquires high-precision 3D point clouds independently of ambient lighting, making it generally more robust than purely vision-based methods under strong sunlight, shadows, and repetitive textures in agricultural fields. More importantly, LiDAR has a certain canopy penetration capability and can exploit gaps between leaves to detect stems, branches, and the ground surface, thereby alleviating the missing ground-point problem common in photogrammetry [107,110–113]. For example, Husin et al. [111] and Bates et

al. [112] showed that both ground-based and aerial LiDAR can effectively capture internal canopy structure for applications including health monitoring, plant height estimation, and yield prediction. In addition to geometric coordinates, modern LiDAR systems often record return intensity, which can be used to distinguish plant organs based on differences in near-infrared reflectance and thereby support stem–leaf separation and the extraction of fine structural traits such as branch angle and stem diameter [114,115]. Su et al. [116] used a Velodyne VLP-16 LiDAR to collect maize point clouds and achieved high-accuracy phenotypic parameter measurement through projection-based segmentation and fitting algorithms. At the same time, because conventional mechanically rotating LiDARs are vulnerable to reliability issues under high-vibration conditions, solid-state and semi-solid-state LiDARs based on MEMS or Flash technologies are gradually becoming important configurations for agricultural ground robots [117].

If RGB and LiDAR primarily address structural perception, spectral and thermal imaging further extend the ability of mobile phenotyping systems to sense plant physiological status. Multispectral imaging typically includes a small number of discrete bands, such as blue, green, red, red-edge, and near-infrared, among which the red-edge band is particularly sensitive to chlorophyll variation. As a result, it is widely used to compute vegetation indices such as NDVI and NDRE for inferring crop nitrogen status, photosynthetic efficiency, and early senescence [102,118,119]. Hyperspectral imaging, by contrast, provides hundreds of contiguous bands and can capture much finer spectral signatures, supporting the inversion of more complex biochemical constituents such as anthocyanins, carotenoids, and leaf water content, while also showing distinct potential for early disease detection and stress-resistance screening [120–124]. For instance, Brown et al. [125] showed that hyperspectral leaf reflectance can identify infected soybean plants before visible symptoms appear and can reveal key physiological changes related to chlorophyll and water content. However, the very high dimensionality of hyperspectral data substantially increases storage, transmission, and real-time processing costs, and therefore typically requires edge-side dimensionality reduction and feature selection strategies [126–128]. Thermal infrared imaging, meanwhile, characterizes transpiration and stomatal conductance through canopy temperature distribution and plays an important role in plant water-stress detection, drought-tolerance screening, and precision irrigation decision-making [102,129–131].

For mobile phenotyping robots, perception is not only about observing plants but also about understanding the surrounding environment and determining the robot's own position. Because real field environments frequently involve GNSS occlusion, abrupt illumination changes, repetitive textures, and terrain-induced disturbance, localization-aware sensing has become a foundational capability for system autonomy [132]. Although RTK-GNSS can provide centimeter-level absolute positioning in open areas, satellite signals often degrade or fail in tall-crop fields and orchards because of canopy blockage and multipath effects [133]. Consequently, modern agricultural robots increasingly rely on fused localization frameworks that integrate wheel odometry, inertial measurement units (IMUs), and visual or LiDAR data, with the IMU providing high-frequency attitude estimation and short-term dynamic compensation, while external sensors correct long-term drift [133–135].

In this context, SLAM has become a key technology for autonomous navigation in agricultural fields. Because lighting conditions in agricultural environments are highly unstable, purely visual SLAM tends to degrade under strong direct sunlight, shadow transitions, and repetitive textures. By contrast, LiDAR SLAM methods such as LOAM, LIO-SAM, and the FAST-LIO family are less dependent on illumination and can exploit geometric priors such as crop-row structure for feature matching, resulting in greater robustness in complex field environments [134,136]. For inter-row navigation, LiDAR point clouds can be used to accurately extract crop-row lines and construct local occupancy maps to support path planning [137,138]. Building on this, an important recent trend is the shift from purely geometric mapping to semantic mapping, in which object detection or semantic segmentation networks are incorporated into SLAM so that point clouds or image regions can be assigned labels such as crop, weed, ground, and obstacle [139,140]. For example, Rapado-Rincon et al. [141] proposed the use of specific reference plants as semantic landmarks to support long-term re-localization and growth

tracking across repeated inspections. Qu et al. [134] combined SegFormer-based semantic segmentation with visual SLAM in greenhouse environments to construct a real-time semantic point-cloud map for safe path generation and precise navigation, while Pan et al. [142] developed a perception and semantic mapping method for orchard robots that significantly improved navigation performance in complex environments. More importantly, such semantic maps are no longer used solely for navigation; they are increasingly coupled directly with phenotypic analysis. For instance, Zheng et al. [143] proposed a multi-RGB-D SLAM framework that constructs maps containing both geometric structure and semantic labels, enabling centimeter-level 3D reconstruction and apple phenotypic parameter extraction in large-scale orchards. Figure 5 summarizes representative methods ranging from GNSS/RTK-assisted localization to LiDAR/SLAM-based mapping and semantic-segmentation-based navigation-line extraction, illustrating the evolution of agricultural robot localization from dependence on absolute positioning toward robust environment-understanding-driven localization.

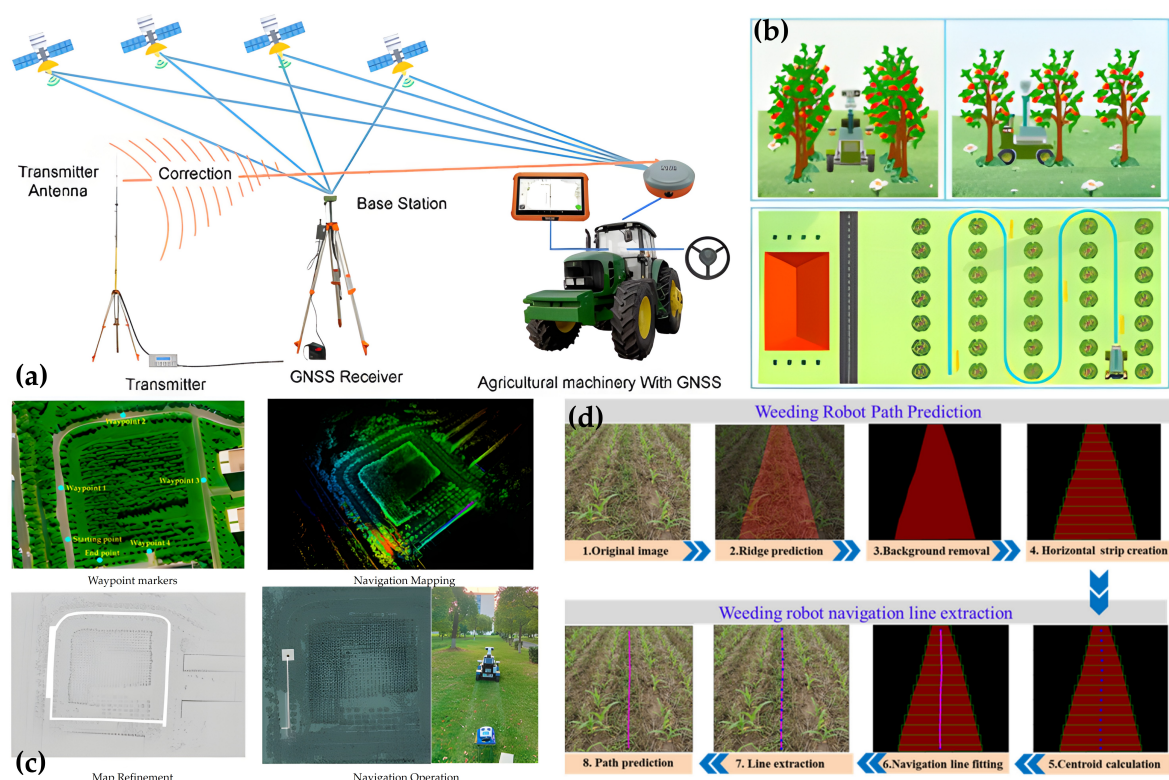


Figure 5. Schematic illustration of operating strategies for mobile phenotyping robots in unstructured field environments. (a) Principle of GNSS-RTK positioning [133]; (b) GNSS-RTK-based navigation of an agricultural robot in an orchard environment [134]; (c) LiDAR-based mapping, path planning, and navigation operation [134]; (d) navigation-line extraction based on semantic segmentation [144].

Although single sensors can already support some phenotyping tasks, the combined effects of field occlusion, background clutter, and environmental variation mean that highly reliable phenotyping systems ultimately require multimodal fusion and active vision. The central goal of multimodal fusion is to exploit complementarity across sensing modalities to compensate for the inherent limitations of any single sensor. Recent studies in multimodal representation learning have demonstrated that integrating heterogeneous data sources can significantly improve robustness and semantic understanding in complex environments [145–148]. These advances suggest that multimodal perception architectures originally developed in computer vision and affective computing may also provide useful methodological references for agricultural phenotyping systems. For example, counting green fruits from RGB images alone is highly susceptible to interference from background leaves, whereas incorporating depth information through RGB-D fusion can substantially improve foreground–background separability [149,150]. Wang et al. [151] proposed the RD-SSD model, which fused RGB and depth

images to successfully identify tomatoes occluded by leaves or partially overlapped with neighboring fruits. Similarly, RGB–thermal fusion exploits differences in thermal inertia between fruits and leaves to provide an additional contrast channel for target detection under shadowed or nighttime conditions [152]. In addition, Neural Radiance Fields (NeRF) represent a highly promising direction [153]. The multimodal NeRF framework proposed by Chopra et al. [154] further enhanced target–background separation under complex lighting through cross-spectral scene modeling. At the methodological level, fusion strategies typically include data-level fusion, such as directly inputting depth as an additional channel, and feature-level fusion, in which features are extracted separately from different modalities and then combined. Existing studies indicate that multimodal fusion networks specifically designed for agricultural scenarios can significantly improve detection accuracy for small and occluded targets. For example, Li et al. [155] proposed YOLO-MSRF, which improved mAP50 by 2.3% and mIoU by 3.6% while maintaining good real-time performance; Huang et al. [156] proposed CornMFN, which fused image and meteorological data through cross-attention and improved maize phenological stage recognition accuracy by 6.91% relative to single-modality models.

In complex canopy scenes, passive perception alone is often insufficient to fully resolve severe occlusion, and active vision is therefore becoming an increasingly important complement in mobile phenotyping systems. On the one hand, amodal segmentation learns the complete contour of a target under occlusion and can infer the hidden shape of partially visible objects, thereby reducing bias in fruit counting and size estimation [157–159]. For example, Kim et al. [157] developed a Transformer-based amodal segmentation network that significantly reduced error in fruit size estimation; Yang et al. [158] proposed the ACBET network, which effectively recovered complete tomato shape under occlusion; and Jiang et al. [159] introduced an amodal segmentation framework for heavily occluded soybean pods based on an improved Swin Transformer and SimAM attention, achieving high-accuracy estimation of seeds per pod. On the other hand, when missing information cannot be fully recovered from single-frame inference, robots can actively change their viewpoint through viewpoint planning. In the so-called Next-Best-View (NBV) strategy, the robot drives the chassis or manipulator toward observation positions with higher expected information gain based on unknown regions or entropy distributions in the current 3D model, thereby acquiring supplementary images and progressively refining target reconstruction [150,160]. This shift indicates that perception in mobile phenotyping systems is evolving from passive sampling toward active information acquisition through perception–action coupling.

3.2. Decision: From Motion Planning to Phenotypic Understanding

In mobile phenotyping robots, the decision layer serves as the central bridge between perceptual input and executable output. Its core role can be summarized in two aspects: determining how the robot should move safely and efficiently, and determining how the system should extract biologically meaningful phenotypic information from large volumes of observational data. The former corresponds to motion decision-making and task planning, whereas the latter concerns phenotypic analysis and target understanding. With the development of deep learning, generative artificial intelligence, and foundation models [161–165], these two types of decision-making are becoming increasingly coupled rather than remaining separate. Figure 6 presents representative examples spanning coverage path planning, dynamic obstacle avoidance, image segmentation, temporal point-cloud analysis, real-time onboard detection, and cross-temporal point-cloud registration, showing that the decision layer of agricultural robots now comprises two parallel yet closely intertwined technical threads: motion planning and target understanding.

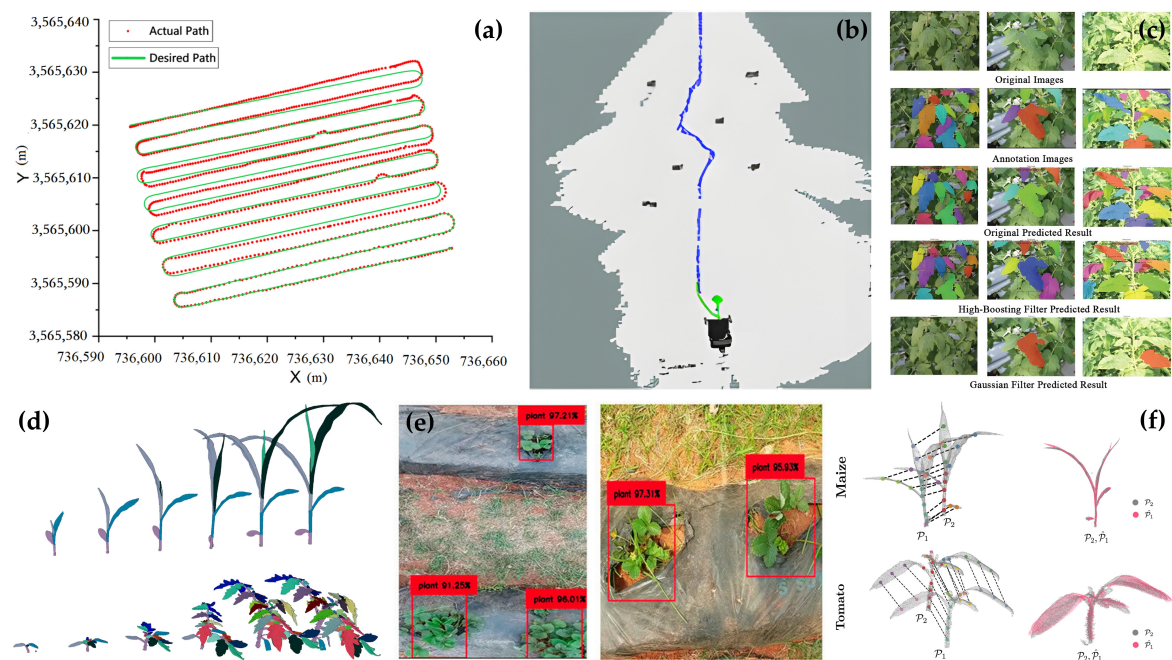


Figure 6. Representative studies illustrating the dual decision-making roles of motion planning and target understanding in mobile phenotyping systems. (a) Field path planning and actual trajectory tracking, showing full-coverage decision-making for inter-row operation and headland turning [166]; (b) dynamic obstacle-avoidance trajectories of an agricultural robot in cluttered environments, demonstrating local environmental perception and real-time path replanning [167]; (c) leaf instance segmentation in greenhouse scenes with complex backgrounds, reflecting plant recognition capability based on detection and segmentation [168]; (d) temporal changes and organ labels in 3D point clouds of tomato plants, illustrating the process of temporal 3D phenotypic analysis [169]; (e) real-time strawberry detection on a greenhouse mobile robot, demonstrating end-to-end recognition on edge devices [170]; (f) point-cloud matching and organ correspondence across time points, indicating that 4D registration can support growth tracking and organ-level dynamic phenotypic analysis [171].

From the perspective of motion decision-making, robot movement in agricultural fields is not merely a geometric navigation problem, but a joint optimization problem involving geometric constraints, dynamic effects, and agronomic requirements. The primary objective of global planning is typically to cover the entire field while minimizing non-working travel, energy consumption, and soil compaction [172]. Algorithmically, the field is often abstracted as a directed graph, and coverage path planning can be formulated as graph traversal or optimization problems such as the Traveling Salesman Problem (TSP). Graph-theoretic studies on path embedding and Hamiltonian properties provide theoretical insights into how feasible traversal paths can be constructed under structural constraints [173,174]. For example, Bochtis et al. [175] adopted this strategy to address agricultural coverage planning. Because agricultural vehicles are constrained by minimum turning radii, headland turning often requires specially designed trajectories, such as Ω -shaped or fishtail patterns, to balance operational efficiency and maneuverability [176]. Local planning, by contrast, is responsible for handling local disturbances and temporary obstacles during execution of the global path. Yang et al. [177] proposed a multi-objective optimization framework combining an improved A* algorithm with a CNN, in which A* uses NDVI maps to guide machinery away from dense vegetation, while the CNN predicts the trajectories of people or vehicles from real-time LiDAR data, thereby jointly optimizing path length, smoothness, and safety in complex field environments. To address energy consumption and soil protection, Vahdanjoo et al. [178] further proposed 3D coverage-planning models such as Soil2Cover, which directly reduce non-working travel and soil compaction damage through optimization of the path graph structure.

If global planning determines where to go and how to achieve complete coverage, then inter-row straight-line navigation and trajectory correction determine whether the robot can move stably through narrow crop rows. In high-density planting scenarios, even small lateral deviations may cause crop

damage or collisions, making crop-row centerline extraction and heading-error correction essential. Current approaches include both traditional machine-vision methods, such as the Hough transform and RANSAC [179–182], and deep-learning-based semantic segmentation methods [137,183]. To cope with missing plants, broken rows, and partial occlusion, studies often incorporate Kalman filtering or particle filtering to smooth row-line estimation and improve the stability of continuous navigation [137,183–185]. At the same time, wet and muddy field surfaces can cause wheel slip, leading to significant discrepancies between commanded and actual motion. Advanced control systems therefore increasingly incorporate slip-rate estimation into the kinematic model by inferring slip in real time from differences among wheel speed, IMU acceleration, and vision- or radar-based velocity, and then actively compensating steering deviations using Model Predictive Control (MPC) or Active Disturbance Rejection Control (ADRC) [93,186,187]. In essence, these methods indicate that motion decision-making in agricultural robotics is evolving from simple geometric centerline tracking toward robust control that explicitly accounts for ground interaction.

Dynamic obstacle avoidance further highlights the distinctive nature of decision-making in agricultural environments. Unlike standard mobile-robot settings dominated by rigid obstacles, field environments often contain both rigid objects, such as rocks, stumps, and farm machinery, and flexible objects, such as extended leaves, weeds, and vines [167,188]. For the former, the robot generally needs to stop or detour, whereas for the latter, direct traversal may in some cases be more efficient. As a result, agricultural robots increasingly require semantic traversability analysis, meaning that they must not only detect the presence of objects ahead, but also infer their physical properties, traversability, and operational risk, and assign different inflation radii and cost weights in the cost map accordingly, so as to generate safe paths better aligned with real operational needs [189,190].

Running in parallel with motion decision-making is a second major thread: deep-learning-based phenotypic analysis decision-making, whose core goal is to convert images, point clouds, and temporal observations into quantitative indicators with agronomic significance. At present, deep learning has become the dominant paradigm in this domain. Single-stage detectors represented by the YOLO family are widely used for real-time counting of fruits, flowers, and similar targets because of their fast inference speed and ease of deployment [191–202]. Liu et al. [203] also confirmed, through a systematic comparison across multiple crop fruit-recognition tasks, the suitability of YOLO-based methods for online perception in agricultural robots. For finer-grained tasks, such as leaf-area measurement, lesion-area estimation, or segmentation of complex boundaries, instance segmentation remains a key tool, with Mask R-CNN and its variants serving as representative methods [204–206]. For example, Barreto et al. [207] achieved end-to-end extraction of leaf area and disease severity from UAV imagery. To address leaf overlap and cluttered backgrounds, recent studies have increasingly emphasized boundary enhancement mechanisms, significantly improving the segmentation of adhered leaves through edge-aware feature fusion [208] or local refinement modules [168]. For disease grading and cultivar identification, lightweight networks such as MobileNetV3 and EfficientNet, combined with attention mechanisms such as SE and CBAM, have also shown strong potential for early agricultural diagnosis [209].

When phenotyping tasks extend from 2D image analysis to 3D plant structural reconstruction, the decision problem correspondingly shifts from target recognition to structure interpretation. In 3D point-cloud processing, networks such as PointNet++ [210] and PointSegNet [211] can perform point-wise semantic classification, assigning labels such as stem, leaf, or ground to each point. On this basis, clustering can then be used to complete instance segmentation, enabling automated measurement of organ-level traits such as leaf length, leaf width, leaf angle, and stem diameter [212–215]. To further quantify branching topology, researchers often simplify point clouds into skeletal representations. More recently, Denoising Diffusion Probabilistic Models (DDPMs) have also been introduced into skeleton extraction, allowing systems to recover missing connections and reconstruct more complete topological structures based on learned plant morphological priors, even when point clouds are severely incomplete [216,217]. More importantly, plant phenotypes are inherently dynamic rather

than static. As a result, 4D reconstruction and temporal tracking are becoming increasingly important research directions. By registering 3D models acquired at multiple time points, researchers can construct cross-temporal 4D point clouds and use Transformer-based spatiotemporal models to learn plant growth patterns, thereby enabling missing-time-point completion, growth-trend prediction, and even yield estimation [95,218,219].

It is also important to note that conventional deep-learning models typically rely heavily on manually annotated data, whereas agricultural annotation is costly, category-diverse, and subject to strong environmental variation, making model generalization a recurring bottleneck [220]. In this context, foundation models and generative artificial intelligence are beginning to reshape the technical landscape of phenotypic analysis decision-making. Applications of the Segment Anything Model (SAM) in agriculture have shown that large-scale pretrained segmentation models can effectively alleviate annotation bottlenecks in open-set scenarios and improve segmentation generalization in agricultural environments [221–224]. Ongoing efforts to adapt SAM to agriculture, such as WheatSAM [225] and text-prompted segmentation frameworks combined with Grounding DINO [226], have further demonstrated the potential for crop-organ segmentation under zero-shot or few-shot conditions. At the same time, generative models such as Stable Diffusion and GANs are increasingly being used to mitigate agricultural data scarcity and class imbalance. In 2D applications, Muhammad et al. [227] used diffusion models to generate leaf images with specific disease characteristics to alleviate sample insufficiency in disease recognition. In 3D applications, Roggiolani et al. [228] further explored the generation of synthetic plant point clouds with realistic geometric characteristics for model pretraining and robustness enhancement. Overall, AIGC is gradually evolving from a data-augmentation tool into an important enabling technology for improving the generalization capability of agricultural vision models [157].

3.3. Action: From Stable Mobility to Active Intervention

If perception and decision-making determine whether a robot can understand its environment and targets, then the action layer determines whether that understanding can be translated into behavior in the physical world. For mobile phenotyping systems, action is not limited to moving the chassis from one location to another; rather, it encompasses a broader set of physical interaction capabilities, including terrain adaptation, posture stabilization, viewpoint adjustment, target contact, and active intervention. It is precisely at this level that the distinctive value of ground robots, relative to traditional UAV-based remote sensing or fixed platforms, becomes fully evident.

The chassis system first determines which operating environments the robot can enter and with what level of stability it can perform observation tasks. Wheeled chassis are structurally simple, energy efficient, and easy to maintain, making them well suited for rapid movement in relatively flat and dry fields. Designs with four-wheel independent steering can further enable zero-radius or small-radius turning, thereby significantly improving maneuverability in narrow headland environments [229–231]. Tracked chassis, by contrast, provide larger ground-contact area, lower ground pressure, and stronger traction, and therefore offer better traversability and stability in complex environments such as wet soft soils, paddy fields, or steep orchards [93,232]. Studies have shown that under combined slope and moisture stress, tracked platforms generally exhibit substantially lower slip rates than wheeled systems and are less prone to immobilization or severe skidding [186,229]. For more extreme uneven terrain or obstacle-crossing requirements, wheel-leg hybrid platforms and quadruped-inspired robots are also beginning to enter agricultural applications. These systems can actively regulate body height and posture to maintain sensor stability and chassis traversability, although their energy consumption, control complexity, and endurance remain major constraints on practical deployment [233,234].

Once the chassis enters complex terrain, an appropriate mechanical configuration alone is not sufficient to ensure stable operation; traction management and vibration isolation at the control level are equally critical. In particular, under muddy or low-adhesion conditions, simple PID control often cannot adequately handle slip. More advanced control frameworks therefore commonly incorporate traction control systems (TCS), which estimate slip rate in real time by comparing wheel speed with

actual vehicle speed and dynamically adjust motor torque distribution or differential strategies when slip is detected, thereby maintaining platform stability and trajectory-tracking performance [186,235]. In addition, active suspension systems can be used to isolate high-frequency vibrations and ground impacts, protecting precision devices such as cameras, LiDAR, and spectral sensors and reducing image blur and sensor drift that would otherwise degrade phenotypic data quality [229]. This indicates that chassis control in agricultural robotics is not independent of the sensing task, but is directly linked to observation stability and data reliability.

Beyond stable mobility itself, a more distinctive value of mobile robots lies in their ability to actively modify observation conditions. When fruits, ears, or leaves are occluded within the canopy, robotic arms mounted on the platform can use preliminary perception results to actively adjust the camera viewpoint, capturing supplementary images from side, bottom, or other unconventional perspectives in order to construct more complete 3D models and improve counting and size-estimation accuracy [150,160]. Such strategies, which combine perception and adjustment in real time, effectively incorporate action into the phenotypic information acquisition process, transforming the robot from a passive sampling device into an intelligent system that actively optimizes observation conditions. More importantly, robotic manipulators can also perform controlled physical interaction with the environment, thereby overcoming the limitations of conventional non-contact observation. For example, when fruit is completely occluded by leaves, an end effector can plan a collision-free trajectory under visual guidance, gently move the leaves aside to expose the hidden target for imaging, and then restore them to minimize disturbance to the crop [236]. In essence, this type of interactive perception strategy mimics the action logic of human agronomists during field inspection and can improve data completeness without substantially increasing the risk of crop damage. In addition, certain key traits cannot be reliably obtained through vision alone and instead require contact-based measurement. For example, stem mechanical strength must be assessed through the application of physical force [237]. Likewise, some physiological and biochemical traits of leaves can be measured using robotic-arm-mounted fiber-optic probes such as LeafSpec, which are placed directly against the leaf surface to collect high signal-to-noise spectral data while eliminating ambient light interference [238]. Beyond measurement, robotic manipulators can also perform automated tissue sampling, thereby supplying material for downstream molecular analysis and phenotype–genotype association studies [239]. From a long-term perspective, therefore, the action system of mobile phenotyping robots is not merely an auxiliary module for navigation and supplementary imaging, but a key enabler for shifting plant phenotyping from observational workflows toward interactive and operational paradigms.

3.4. Field Deployment: Edge Computing and Engineering Challenges in Agricultural Environments

If the sensing, decision-making, and action capabilities described above cannot operate stably over extended periods in real field environments, their academic value is unlikely to translate into practical utility. For mobile phenotyping robots, deployment is not merely a matter of software transfer, but a systems engineering problem involving computation, thermal management, communication, and energy management. For this reason, field deployability is increasingly becoming a key criterion for assessing the practical potential of agricultural robots.

First, edge computing is a prerequisite for real-time operation in mobile phenotyping systems [240,241]. Agricultural robots often operate under unstable or even absent network connectivity, while simultaneously requiring millisecond-level responses to dynamic obstacles, target detection, and path adjustment. Under such conditions, heavy reliance on cloud computing is generally impractical. Data acquisition, preprocessing, inference, and part of the decision process must therefore be executed locally on edge devices. At present, NVIDIA Jetson platforms, such as Jetson Orin NX and AGX Orin, have become important hardware foundations for edge deployment in agricultural robotics by offering strong AI inference capability at relatively low power consumption (15W–60W) [85,242]. For example, Shuai et al. [243] achieved real-time weed detection in soybean fields on a Jetson Orin platform at 59 FPS while maintaining power consumption at 65 W. Similarly, the GTDR-YOLOv12 model proposed by Yang et al. [244] and the lightweight model developed by Qi et al. [245] both demonstrated

effective deployment of Jetson platforms for agricultural vision tasks. Compared with CPU-dominated platforms such as Raspberry Pi 5, Jetson Orin typically provides order-of-magnitude advantages for complex vision workloads and is therefore better suited to the high-throughput inference demands of modern mobile phenotyping systems [246].

However, the adoption of foundation models and high-complexity deep networks also introduces a dual challenge for edge deployment in terms of model size and computational burden, making model compression and lightweight design unavoidable technical directions. Quantization is among the most common solutions, using tools such as TensorRT and Quantization-Aware Training (QAT) to compress model weights from FP32 to FP16 or even INT8 [5,247]. Existing studies have shown that INT8 quantization can typically reduce model size by about fourfold and increase inference speed by 3–8×, while keeping accuracy loss within 1%, making it well suited to real-time field applications [247,248]. Wu et al. [249] further demonstrated that structured pruning can more than double inference speed with almost no loss in accuracy, highlighting the practical value of pruning for agricultural edge devices. Beyond compressing existing models, another important strategy is to design lightweight architectures specifically for edge deployment. For instance, Xu et al. [250] proposed RSCDet, which uses structural optimizations such as RepGhostConv and channel compression to achieve real-time inference at 35 FPS on Jetson TX2 NX while maintaining aphid counting accuracy above 84.5%. Overall, advances in edge computing are driving mobile phenotyping systems from offline analysis platforms toward online closed-loop systems [250,251].

Beyond computation itself, engineering constraints imposed by field environments also profoundly affect system reliability. Among them, thermal management is one of the most common yet underestimated issues. Agricultural robots often operate for extended periods under high temperatures, direct sunlight, and dusty conditions, while high-performance chips generate substantial heat under full load. Without adequate thermal control, the system may throttle or even fail. To address this, existing systems typically combine passive and active cooling strategies, such as using metal enclosures as heat-dissipation structures, installing high-static-pressure industrial fans for forced air cooling, and reducing solar heat load through sunshades or highly reflective coatings [252,253]. At the same time, airflow channels must also be designed for dust and water resistance in order to prevent damage to electronic components from mud and particulate intrusion [252,253]. Communication challenges mainly arise from discontinuous network coverage and heterogeneous data types in large-scale field environments. On the one hand, low-power, long-range communication technologies such as LoRaWAN are well suited for telemetry transmission and status reporting, providing stable low-bandwidth communication over kilometer-scale distances. On the other hand, for video streams or high-throughput phenotypic data, public 5G/4G links are generally preferred. In communication blind spots, systems may switch to low-Earth-orbit satellite links such as Starlink or adopt a store-and-forward strategy based on local buffering and delayed upload to ensure that critical data are not lost [254,255]. This suggests that future communication architectures for mobile phenotyping systems will likely evolve toward multi-link redundancy and task-layered communication design. Finally, energy management directly determines the operating range and endurance of the platform. In addition to high-energy-density lithium batteries, intelligent battery management systems (BMS) are also essential, as they can dynamically regulate the power consumption of sensors and computing units according to task priority, for example by shutting down high-power devices such as LiDAR during standby or low-load periods [232]. For long-endurance missions, hybrid powertrains and lightweight platforms integrated with solar-assisted charging components are also attracting attention, with the goal of achieving a more balanced trade-off between payload and endurance [232]. From an application perspective, the competitiveness of future high-throughput plant phenotyping robots will depend not only on model accuracy or single-experiment performance, but also on their ability to operate continuously, stably, and with low maintenance in real agricultural environments.

4. Discussion

Despite the substantial progress made in recent years in the perception, decision-making, and action capabilities of mobile phenotyping robots, and despite their encouraging performance in many controlled experiments, a series of unresolved systemic bottlenecks still hinder the transition from laboratory validation to real field deployment. These bottlenecks do not stem simply from insufficient accuracy of individual algorithms or limitations of isolated hardware components. Rather, they are manifested in insufficient model generalization under complex environmental variation, the continued scarcity of high-quality annotations and diverse data resources, the lack of unified standards and reproducibility protocols across platforms, and the persistent gap between current systems and the requirements of large-scale, long-term, unattended operation. In other words, the central challenge in mobile phenotyping has shifted from whether a working prototype can be built to whether a technological framework can be established that is cumulative, comparable, and deployable.

4.1. Challenges

First, environmental heterogeneity and limited cross-scenario generalization remain the primary obstacles to the practical deployment of mobile phenotyping systems. In agricultural environments, illumination, climate, season, crop scale, observation viewpoint, and platform height all vary continuously, such that high performance achieved under a single condition often does not transfer directly to new fields, seasons, or platform configurations. Ullah et al. [256] pointed out that when a perception system is transferred from a ground vehicle (GV) perspective to a UAV perspective, model performance can degrade markedly due to substantial changes in plant scale, observation geometry, and illumination patterns. Hu et al. [257], in their review of domain adaptation for large-scale agricultural imaging data, further emphasized that the mismatch between training and testing distributions caused by environmental, seasonal, and sensor differences is fundamentally the main reason for the limited generalization of current agricultural vision models. For systems that rely heavily on passive optical imaging, abrupt illumination variation is especially likely to destabilize feature representations and thus degrade recognition and segmentation performance. Therefore, if future mobile phenotyping systems are to achieve cross-season, cross-region, and cross-platform deployment, cross-domain consistency modeling, unsupervised domain adaptation, and robust representation learning must be elevated from optional performance enhancements to core design requirements [256–258].

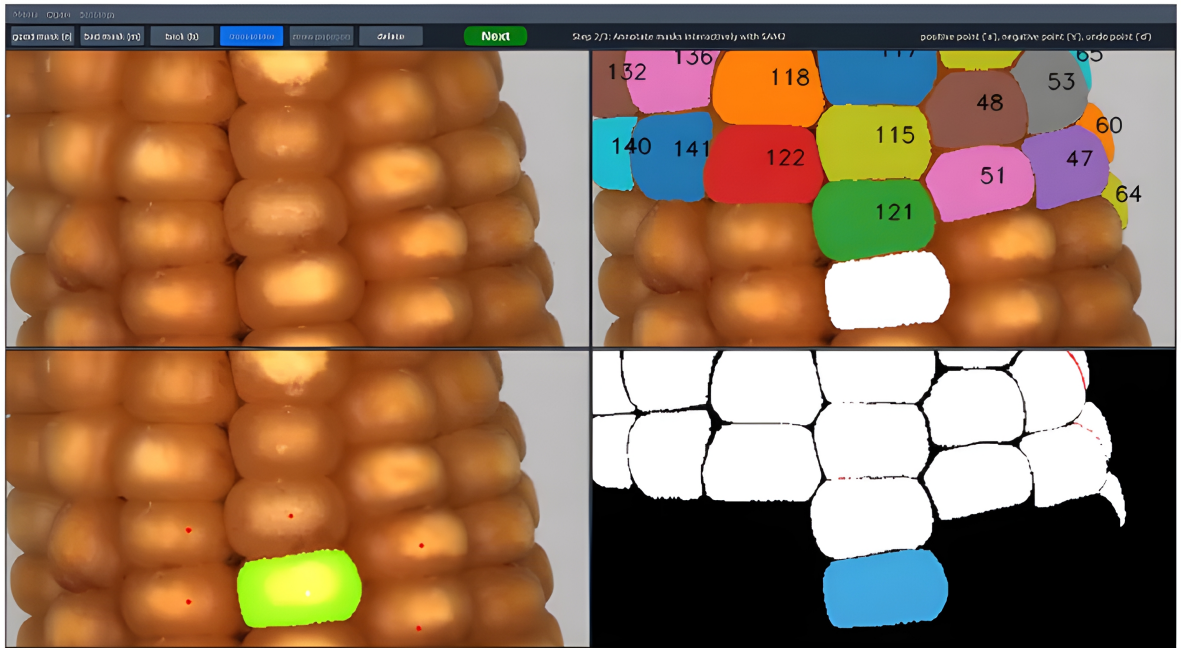


Figure 7. Overview of the ARAMSAM user interface [259]

Second, the scarcity of high-quality data and the high cost of expert annotation remain key bottlenecks limiting the continued advancement of agricultural robotic vision models. Unlike general computer vision tasks, high-precision annotation of plant organs typically requires not only pixel-level or instance-level fine-grained delineation, but also annotators with botanical and agronomic expertise, making the data construction process highly dependent on domain experts and significantly increasing both time and economic costs [260]. More broadly, the complexity of agricultural image data and the high cost of annotation are core constraints on the deeper integration of plant science and deep learning [261]. In response, recent studies have begun exploring semi-automatic annotation workflows with expert involvement. For example, Oehme et al. [259] developed ARAMSAM (Figure 7), which uses the automatic mask generation capability of SAM to pre-annotate agricultural images and, in user studies involving experts, significantly reduced the time required for instance segmentation annotation, indicating that foundation-model-assisted annotation can effectively alleviate the scarcity of expert labeling resources. However, improved annotation efficiency alone is insufficient to fundamentally resolve the data problem, because currently available public datasets remain clearly inadequate in terms of scene diversity, seasonal coverage, sensor variety, and environmental complexity [257]. In this context, synthetic data generated by generative artificial intelligence is emerging as an important complementary solution. Hartley et al. [262] proposed generating plant synthetic images for target domains by combining Stable Diffusion, LoRA, and ControlNet. Such methods can preserve key structural information, such as leaf instances, while achieving cross-domain style transfer, and can improve model generalization in complex field environments at relatively low cost by jointly training on real and synthetic data. This suggests that future high-quality agricultural data ecosystems may increasingly depend not on a single source, but on a composite paradigm integrating real data acquisition, foundation-model-based pre-annotation, and generative-model-based expansion.

The lack of standards and the fragmentation of current research are weakening the efficiency of knowledge accumulation in this field. From a systems perspective, the reliability and diagnosability of distributed computing and robotic systems have long been studied through graph-theoretic models of network connectivity and fault tolerance [263–267]. These studies highlight how structural properties of network topologies influence the robustness and diagnosability of large-scale distributed systems. Existing studies on mobile phenotyping differ substantially in platform configuration, sensor parameters, operating conditions, data-processing pipelines, and evaluation metrics, and are often validated under hardware and experimental settings that are specific to individual groups, making results difficult to compare directly. The consequence of this fragmentation is not merely the difficulty of horizontal comparison; more importantly, it obscures the true extent of methodological progress and makes cross-study meta-analysis and cumulative knowledge building extremely difficult. To address this issue, the community urgently needs unified benchmark datasets, evaluation protocols, and metadata standards tailored to mobile phenotyping. At present, MIAPPE (Minimum Information About a Plant Phenotyping Experiment) [268] is the most representative community-driven metadata standard in plant phenotyping and has been adopted by databases such as BreedBase and PHIS as well as the BrAPI interface, providing strong support for the implementation of FAIR data principles. For mobile robotic phenotyping research, the underlying philosophy of MIAPPE is equally valuable, but the current framework still needs to be extended to cover hardware- and system-level metadata, including robot kinematic parameters, platform configuration, sensor mounting arrangements, imaging geometry, and control software versions. Only under such conditions can data from different platforms and laboratories become truly integrable and reusable.

More broadly, standardization should not be limited to unifying data formats; reproducibility should also be treated as a fundamental requirement rather than an added value. One promising direction is the systematic release of standardized annotated datasets, hardware and software configurations, and complete source code for deep learning models [261]. At present, many studies report algorithmic performance metrics but do not provide complete access to model weights, inference code, hardware specifications, data-preprocessing workflows, or deployment details, making it difficult

for external researchers to independently reproduce and objectively verify the results. Drawing on established practices in computer vision and genomics, future mobile phenotyping research should at minimum systematically disclose the following: sensor models and calibration parameters, robot chassis kinematic parameters and control software versions, tested model weights and inference interfaces, and complete data-processing pipelines. The reproducibility tiering framework for machine learning in the life sciences proposed by Heil et al. [269] offers a valuable reference in this regard.

4.2. Future Perspectives

Beyond these challenges, the future direction of mobile phenotyping is becoming increasingly clear. Overall, progress will not be driven simply by improving the performance of individual platforms, but by moving toward larger-scale system collaboration, stronger online intelligence, and deeper autonomous decision-making.

First, for large-scale breeding trials and long-term field monitoring, single-platform systems and even simple UAV–UGV dual-platform frameworks are approaching their efficiency limits. Multi-robot collectives are therefore likely to become a key pathway for improving throughput, redundancy, and task resilience. For phenotyping tasks spanning hundreds of hectares or more, the system must not only collect data more efficiently, but also tolerate failures, communication interruptions, and local environmental disturbances. In this context, Multi-robot coordination is no longer merely an extension of running multiple machines in parallel; instead, it becomes a distributed systems problem involving communication reliability, fault detection, and cooperative task allocation. In large-scale distributed computing systems, similar challenges have long been addressed through diagnosability and connectivity analysis in interconnection networks [270–272]. These theoretical insights provide useful perspectives for improving the robustness of heterogeneous robotic collectives operating in agricultural environments; rather, it becomes a systems engineering problem involving decentralized communication, heterogeneous task allocation, conflict resolution, and fleet-level energy management. The MARbLE platform proposed by Boubin et al. [273] showed that, in digital agriculture, multi-robot systems can accelerate task execution and reduce energy consumption through online learning and information sharing when combined with edge-computing nodes and multi-agent reinforcement learning (MARL). Zhu et al. [274] further introduced large language models (LLMs) into UAV-assisted edge-computing networks to enhance multi-agent coordination, enabling adaptive task offloading and cross-region load balancing. Similarly, the COHERENT system proposed by Liu et al. [275] uses a propose–execute–feedback–adjust (PEFA) mechanism to decompose and allocate complex long-horizon tasks in real time to heterogeneous agents, including UAVs, quadruped robots, and manipulators, and significantly outperforms conventional methods in both task success rate and execution efficiency. Together, these studies suggest that future high-throughput plant phenotyping systems are likely to evolve from single-robot platforms into heterogeneous robotic collectives, supported by 5G communication, distributed edge computing, MARL, and LLM-driven high-level task planning [273–276].

Second, the capability boundary of mobile phenotyping robots is expanding from automated data acquisition toward active understanding and adaptive observation. Most current systems still function essentially as mobile sensor carriers: they collect data along predefined routes and then rely on offline algorithms for analysis, while lacking the ability to actively interpret the biological significance of crop status or to dynamically adjust sampling strategies based on immediate observations. Human agronomists, by contrast, do not work in this way. They routinely determine what to inspect next and how to measure it based on local symptoms, historical growth status, and current environmental conditions. Embodied intelligence seeks to create a tighter coupling among perception, cognition, and action, such that robots are no longer merely platforms that transport sensors, but intelligent agents capable of understanding task intent, recognizing biological anomalies, and proactively adjusting their behavior [277,278]. The core logic of this direction can be summarized as a continuous chain of embodied perception, embodied cognition, embodied execution, and embodied evolution, in which multimodal foundation models handle high-level semantic understanding and task planning,

while lower-level control networks translate those intentions into executable actions in real time [279]. Within this framework, Vision–Language–Action (VLA) models are widely regarded as one of the most promising technical directions for integrating perception, reasoning, and manipulation in robotic systems. Recent studies have explored adaptive decision-making mechanisms for long-horizon robotic tasks through symmetry-aware or language-guided policies [280]. Such frameworks indicate that multimodal reasoning models may eventually enable agricultural robots to autonomously determine sensing strategies, adjust viewpoints, and perform targeted phenotypic observations. VLA models can directly map natural-language instructions and visual observations into robotic action sequences, thereby giving robots stronger generalization ability for complex long-horizon tasks [281]. In agricultural phenotyping, this implies that future robots may be able to autonomously decide whether to switch sensors, adjust viewpoints, perform additional local scanning, or trigger further operations based on observed leaf chlorosis, abnormal plant architecture, or disease symptoms. At the same time, this prospect is constrained by reality: VLA systems typically require substantial computational and memory resources, whereas mobile agricultural robots face strict constraints in size, power, and thermal dissipation [282,283]. Accordingly, the key challenge for future research is not simply to introduce VLA into agriculture, but to explore how to retain its multimodal understanding and task generalization capability while developing architectures that are lighter, more efficient, and capable of stable edge deployment. It is therefore foreseeable that, with deeper integration of embodied intelligence frameworks, multimodal foundation models, and agricultural robotic control systems, future mobile phenotyping platforms will gradually evolve from perception systems into integrated cognition–decision–action systems and assume a more proactive role in precision agriculture and crop breeding.

5. Conclusions

Ground robots are reshaping the technological boundaries of high-throughput plant phenotyping. Compared with aerial platforms designed primarily for large-area scanning and canopy-scale observation, ground robots can enter crop rows and under-canopy environments to acquire higher-resolution, higher-information-density data through close-range, multi-view, and high-payload operation. This capability extends plant phenotyping from remote observation alone toward autonomous sensing, motion decision-making, and active interaction in complex field environments. This review examined the development of mobile phenotyping platforms, with particular emphasis on the role of ground robots in high-throughput plant phenotyping. Major advances were summarized across platform configuration, sensing modalities, localization and mapping, multimodal fusion, motion planning, phenotypic analysis, active observation, robotic intervention, and edge deployment. The importance of ground robots lies not only in improving acquisition throughput, but also in integrating spatial scale, temporal continuity, environmental adaptability, and physical interaction within a unified technical framework, thereby enabling finer analysis of organ-level traits, under-canopy structures, and dynamic growth processes. At the same time, real-world deployment still depends on overcoming several persistent bottlenecks, including robust generalization under complex field conditions, sustained access to high-quality data and annotations, cross-platform standardization and reproducibility, and the engineering reliability required for long-term unattended operation. As air–ground collaboration, multi-robot systems, embodied intelligence, and foundation models continue to advance, mobile phenotyping platforms are expected to evolve from data-acquisition tools into autonomous systems capable of understanding crop status, organizing observation workflows, and supporting long-term field management. In this sense, high-throughput plant phenotyping will become not only a means of collecting data faster, but also a key link between crop biological understanding, robotic autonomy, and precision agriculture.

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References

1. Wang, R.F.; Qu, H.R.; Su, W.H. From sensors to insights: Technological trends in image-based high-throughput plant phenotyping. *Smart Agricultural Technology* **2025**, p. 101257.
2. Pörtner, H.O.; Roberts, D.C.; Adams, H.; Adler, C.; Aldunce, P.; Ali, E.; Begum, R.A.; Betts, R.; Kerr, R.B.; Biesbroek, R.; et al. *Climate Change 2022: Impacts, Adaptation and Vulnerability*; Cambridge University Press: Cambridge, UK and New York, NY, USA, 2022.
3. Furbank, R.T.; Tester, M. Phenomics—technologies to relieve the phenotyping bottleneck. *Trends in plant science* **2011**, *16*, 635–644.
4. Araus, J.L.; Cairns, J.E. Field high-throughput phenotyping: the new crop breeding frontier. *Trends in plant science* **2014**, *19*, 52–61.
5. Wang, Z.; Zhang, H.W.; Dai, Y.Q.; Cui, K.; Wang, H.; Chee, P.W.; Wang, R.F. Resource-efficient cotton network: A lightweight deep learning framework for cotton disease and pest classification. *Plants* **2025**, *14*, 2082.
6. Cui, K.; Tang, W.; Zhu, R.; Wang, M.; Larsen, G.D.; Pauca, V.P.; Alqahtani, S.; Yang, F.; Segurado, D.; Fine, P.; et al. Efficient localization and spatial distribution modeling of canopy palms using uav imagery. *IEEE Transactions on Geoscience and Remote Sensing* **2025**.
7. Lammerts van Bueren, E.T.; Struik, P.C.; van Eekeren, N.; Nuijten, E. Towards resilience through systems-based plant breeding. A review. *Agronomy for sustainable development* **2018**, *38*, 42.
8. Xie, C.; Yang, C. A review on plant high-throughput phenotyping traits using UAV-based sensors. *Computers and Electronics in Agriculture* **2020**, *178*, 105731.
9. Hartmann, A.; Czaundera, T.; Hoffmann, R.; Stein, N.; Schreiber, F. HTPPheno: an image analysis pipeline for high-throughput plant phenotyping. *BMC bioinformatics* **2011**, *12*, 148.
10. West, D.; Lubbers, E.; Wan, S.J.; Khanal, S.; Davis, R.; Jones, D.; da Silva, M.B.; Kumar, P.; Suassuna, N.; Paterson, A.H.; et al. Linkage drag associated with introgression of *Meloidogyne incognita* resistant genes from wild relatives into upland cotton. *Industrial Crops and Products* **2025**, *236*, 121936.
11. White, J.W.; Andrade-Sanchez, P.; Gore, M.A.; Bronson, K.F.; Coffelt, T.A.; Conley, M.M.; Feldmann, K.A.; French, A.N.; Heun, J.T.; Hunsaker, D.J.; et al. Field-based phenomics for plant genetics research. *Field Crops Research* **2012**, *133*, 101–112.
12. Wan, S.J.; Khanal, S.; Brown, N.; Kumar, P.; West, D.M.; Lubbers, E.; Kothari, N.; Jones, D.; Hinze, L.L.; Udall, J.A.; et al. Phenotypic Validation of the Cotton Fiber Length QTL, qFL-Chr. 25, and Its Impact on AFIS Fiber Quality. *Plants* **2025**, *14*, 1937.
13. Li, Z.; Sun, C.; Wang, H.; Wang, R.F. Hybrid optimization of phase masks: Integrating Non-Iterative methods with simulated annealing and validation via tomographic measurements. *Symmetry* **2025**, *17*, 530.
14. Zhou, G.; Wang, R.F.; Cui, K. A Local Perspective-based Model for Overlapping Community Detection. In Proceedings of the 2025 IEEE International Conference on Systems, Man, and Cybernetics (SMC). IEEE, 2025, pp. 2965–2970.
15. Zhou, G.; Wang, R.F. The heterogeneous network community detection model based on self-attention. *Symmetry* **2025**, *17*, 432.

16. Zeng, S.; Qi, D.; Chang, X.; Xiong, F.; Xie, S.; Wu, X.; Liang, S.; Xu, M.; Wei, X. JanusVLN: Decoupling Semantics and Spatiality with Dual Implicit Memory for Vision-Language Navigation. *arXiv preprint arXiv:2509.22548* **2025**.
17. Ting, T.C.; Mackay, D.S.; Jung, J.; Reynolds, M.P.; Yang, Y.; Wang, D.R. Beyond high-throughput: leveraging plant phenotyping to improve understanding and prediction of plant growth through process-based models. *New Phytologist* **2026**.
18. Atefi, A.; Ge, Y.; Pitla, S.; Schnable, J. Robotic technologies for high-throughput plant phenotyping: Contemporary reviews and future perspectives. *Frontiers in plant science* **2021**, *12*, 611940.
19. Di, X.; Cui, K.; Wang, R.F. Toward efficient uav-based small object detection: A lightweight network with enhanced feature fusion. *Remote Sensing* **2025**, *17*, 2235.
20. Cui, K.; Zhu, R.; Wang, M.; Tang, W.; Larsen, G.D.; Pauca, V.P.; Alqahtani, S.; Yang, F.; Segurado, D.; Lutz, D.A.; et al. Detection and Geographic Localization of Natural Objects in the Wild: A Case Study on Palms. In Proceedings of the IJCAI. International Joint Conferences on Artificial Intelligence Organization, 8 2025, pp. 9601–9609. AI and Social Good, <https://doi.org/10.24963/ijcai.2025/1067>.
21. Wang, T.; Tong, R.; Xu, T.; Li, Y.; Chen, Y. Artificial intelligence in plant science: from image-based phenotyping to yield and trait prediction. *Frontiers in Plant Science* **2026**, *16*, 1732979.
22. Khuimphukhieo, I.; da Silva, J.A. Unmanned aerial systems (UAS)-based field high throughput phenotyping (HTP) as plant breeders' toolbox: a comprehensive review. *Smart Agricultural Technology* **2025**, *11*, 100888.
23. Angidi, S.; Madankar, K.; Tehseen, M.M.; Bhatla, A. Advanced high-throughput phenotyping techniques for managing abiotic stress in agricultural crops—A comprehensive review. *Crops* **2025**, *5*, 8.
24. Lee, K.; Han, X. A study on leveraging unmanned aerial vehicle collaborative driving and aerial photography systems to improve the accuracy of crop phenotyping. *Remote Sensing* **2023**, *15*, 3903.
25. Yang, Z.Y.; Xia, W.K.; Chu, H.Q.; Su, W.H.; Wang, R.F.; Wang, H. A comprehensive review of deep learning applications in cotton industry: From field monitoring to smart processing. *Plants* **2025**, *14*, 1481.
26. Xu, R.; Li, C. A review of high-throughput field phenotyping systems: Focusing on ground robots. *Plant phenomics* **2022**.
27. Ahmed, W.A.; Yan, D.; Hamed, J.O.; Olatoyinbo, S.F. Advances in UAV-based deep learning for cassava disease monitoring and detection: A comprehensive review of models, imaging techniques, and agricultural applications. *Smart Agricultural Technology* **2025**, p. 101400.
28. Farella, A.; Paciolla, F.; Quartarella, T.; Pascuzzi, S. Agricultural unmanned ground vehicle (UGV): a brief overview. In Proceedings of the International Symposium on Farm Machinery and Processes Management in Sustainable Agriculture. Springer, 2024, pp. 137–146.
29. Bechar, A.; Vigneault, C. Agricultural robots for field operations: Concepts and components. *Biosystems engineering* **2016**, *149*, 94–111.
30. Kunze, L.; Hawes, N.; Duckett, T.; Hanheide, M.; Krajník, T. Artificial intelligence for long-term robot autonomy: A survey. *IEEE Robotics and Automation Letters* **2018**, *3*, 4023–4030.
31. Chen, C.; Ma, Y.; Dong, B.; Cao, J. DMNR: Unsupervised de-noising of point clouds corrupted by airborne particles. *arXiv preprint arXiv:2305.05991* **2023**.
32. Ren, Z.; Zheng, H.; Chen, J.; Chen, T.; Xie, P.; Xu, Y.; Deng, J.; Wang, H.; Sun, M.; Jiao, W. Integrating UAV, UGV and UAV-UGV collaboration in future industrialized agriculture: Analysis, opportunities and challenges. *Computers and Electronics in Agriculture* **2024**, *227*, 109631.
33. Esser, F.; Rosu, R.A.; Cornelißen, A.; Klingbeil, L.; Kuhlmann, H.; Behnke, S. Field robot for high-throughput and high-resolution 3d plant phenotyping: Towards efficient and sustainable crop production. *IEEE Robotics & Automation Magazine* **2023**, *30*, 20–29.
34. Xie, P.; Ma, Z.; Du, R.; Yang, X.; Jiang, Y.; Cen, H. An unmanned ground vehicle phenotyping-based method to generate three-dimensional multispectral point clouds for deciphering spatial heterogeneity in plant traits. *Molecular Plant* **2024**, *17*, 1624–1638.
35. Wang, R.F.; Tu, Y.H.; Li, X.C.; Chen, Z.Q.; Zhao, C.T.; Yang, C.; Su, W.H. An intelligent robot based on optimized yolov11l for weed control in lettuce. In Proceedings of the 2025 ASABE Annual International Meeting. American Society of Agricultural and Biological Engineers, 2025, p. 1.
36. Selby, P.; Abbeloos, R.; Backlund, J.E.; Basterrechea Salido, M.; Bauchet, G.; Benites-Alfaro, O.E.; Birkett, C.; Calaminos, V.C.; Carceller, P.; Cornut, G.; et al. BrAPI—an application programming interface for plant breeding applications. *Bioinformatics* **2019**, *35*, 4147–4155.
37. Munasinghe, I.; Perera, A.; Deo, R.C. A comprehensive review of uav-ugv collaboration: Advancements and challenges. *Journal of Sensor and Actuator Networks* **2024**, *13*, 81.

38. Nakama, J.; Parada, R.; Matos-Carvalho, J.P.; Azevedo, F.; Pedro, D.; Campos, L. Autonomous environment generator for UAV-based simulation. *Applied Sciences* **2021**, *11*, 2185.
39. Rodriguez, V.; Tipantuña, C.; Reinoso, D.; Carvajal-Rodriguez, J.; Egas Acosta, C.; Proaño, P.; Hesselbach, X. An experimental tethered uav-based communication system with continuous power supply. *Future Internet* **2025**, *17*, 273.
40. Xiang, L.; Gai, J.; Bao, Y.; Yu, J.; Schnable, P.S.; Tang, L. Field-based robotic leaf angle detection and characterization of maize plants using stereo vision and deep convolutional neural networks. *Journal of Field Robotics* **2023**, *40*, 1034–1053.
41. Cui, L.; Le, F.; Xue, X.; Sun, T.; Jiao, Y. Design and experiment of an agricultural field management robot and its navigation control system. *Agronomy* **2024**, *14*, 654.
42. Sun, H.; Chu, H.Q.; Qin, Y.M.; Hu, P.; Wang, R.F. Empowering Smart Soybean Farming with Deep Learning: Progress, Challenges, and Future Perspectives. *Agronomy* **2025**, *15*, 1831.
43. Li, Y.; Deng, G.; Zhao, H.; Liu, B.; Liu, C.; Qian, W.; Qiao, X. A review of UAV remote sensing technology applications in common gramineous crops. *Information Processing in Agriculture* **2026**.
44. Ahmed, W.A.; Ojerinde, J.S.; Olatoyinbo, S.F.; Ogaleye, F.J. UAV Technologies for Precision Agriculture: Capabilities, Constraints, and Deployment Models for Smallholder Systems in Sub-Saharan Africa. *Drones* **2026**.
45. Lu, J.; Qi, Q.; Zheng, G.; Eitel, J.U.; Zhang, Q.; Zhang, J.; Chen, S.; Zhang, F.; Fang, W.; Guan, Z.; et al. High-throughput field phenotyping using unmanned aerial vehicles (UAVs) for rapid estimation of photosynthetic traits. *Plant Phenomics* **2025**, *7*, 100045.
46. Tsouros, D.C.; Bibi, S.; Sarigiannidis, P.G. A review on UAV-based applications for precision agriculture. *Information* **2019**, *10*, 349.
47. Feng, L.; Chen, S.; Zhang, C.; Zhang, Y.; He, Y. A comprehensive review on recent applications of unmanned aerial vehicle remote sensing with various sensors for high-throughput plant phenotyping. *Computers and electronics in agriculture* **2021**, *182*, 106033.
48. Bendig, J.; Bolten, A.; Bennertz, S.; Broscheit, J.; Eichfuss, S.; Bareth, G. Estimating biomass of barley using crop surface models (CSMs) derived from UAV-based RGB imaging. *Remote sensing* **2014**, *6*, 10395–10412.
49. Holman, F.H.; Riche, A.B.; Michalski, A.; Castle, M.; Wooster, M.J.; Hawkesford, M.J. High throughput field phenotyping of wheat plant height and growth rate in field plot trials using UAV based remote sensing. *Remote Sensing* **2016**, *8*, 1031.
50. Sims, D.A.; Gamon, J.A. Relationships between leaf pigment content and spectral reflectance across a wide range of species, leaf structures and developmental stages. *Remote sensing of environment* **2002**, *81*, 337–354.
51. Cui, K.; Li, R.; Polk, S.L.; Lin, Y.; Zhang, H.; Murphy, J.M.; Plemmons, R.J.; Chan, R.H. Superpixel-based and spatially regularized diffusion learning for unsupervised hyperspectral image clustering. *IEEE Transactions on Geoscience and Remote Sensing* **2024**, *62*, 1–18.
52. Li, R.; Cui, K.; Chan, R.H.; Plemmons, R.J. Classification of hyperspectral images using SVM with shape-adaptive reconstruction and smoothed total variation. In Proceedings of the IGARSS 2022-2022 IEEE international geoscience and remote sensing symposium. IEEE, 2022, pp. 1368–1371.
53. Shao, G.; Han, W.; Zhang, H.; Zhou, B.; Wang, Y.; Zhang, Y.; Zhang, L.Y.; Niu, Y.; Xue, Q. Enhancing maize aboveground biomass estimation through time-series UAV-based multispectral and thermal imagery and improved FAO66 model. *International Journal of Remote Sensing* **2026**, pp. 1–21.
54. Liu, T.; Zhu, S.; Yang, T.; Zhang, W.; Xu, Y.; Zhou, K.; Wu, W.; Zhao, Y.; Yao, Z.; Yang, G.; et al. Maize height estimation using combined unmanned aerial vehicle oblique photography and LIDAR canopy dynamic characteristics. *Computers and Electronics in Agriculture* **2024**, *218*, 108685.
55. Tokekar, P.; Vander Hook, J.; Mulla, D.; Isler, V. Sensor planning for a symbiotic UAV and UGV system for precision agriculture. *IEEE transactions on robotics* **2016**, *32*, 1498–1511.
56. Lytridis, C.; Kaburlasos, V.G.; Pachidis, T.; Manios, M.; Vrochidou, E.; Kalampokas, T.; Chatzistamatis, S. An overview of cooperative robotics in agriculture. *Agronomy* **2021**, *11*, 1818.
57. Hall, D.; Dayoub, F.; Kulk, J.; McCool, C. Towards unsupervised weed scouting for agricultural robotics. In Proceedings of the 2017 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2017, pp. 5223–5230.
58. Fan, Z.; Sun, N.; Qiu, Q.; Li, T.; Zhao, C. A high-throughput phenotyping robot for measuring stalk diameters of maize crops. In Proceedings of the 2021 IEEE 11th annual international conference on CYBER technology in automation, control, and intelligent systems (CYBER). IEEE, 2021, pp. 128–133.

59. Li, W.; Yang, F.; Mao, E.; Shao, M.; Sui, H.; Du, Y. Design and verification of crab steering system for high clearance self-propelled sprayer. *Agriculture* **2022**, *12*, 1893.
60. Sivakumar, A.N.; Modi, S.; Gasparino, M.V.; Ellis, C.; Velasquez, A.E.B.; Chowdhary, G.; Gupta, S. Learned visual navigation for under-canopy agricultural robots. *arXiv preprint arXiv:2107.02792* **2021**.
61. Xu, R.; Li, C. A modular agricultural robotic system (MARS) for precision farming: Concept and implementation. *Journal of Field Robotics* **2022**, *39*, 387–409.
62. Li, Z.; Xu, R.; Li, C.; Munoz, P.; Takeda, F.; Leme, B. In-field blueberry fruit phenotyping with a MARS-PhenoBot and customized BerryNet. *Computers and Electronics in Agriculture* **2025**, *232*, 110057.
63. DeBruin, J.; Aref, T.; Tirado Tolosa, S.; Hensley, R.; Underwood, H.; McGuire, M.; Soman, C.; Nystrom, G.; Parkinson, E.; Li, C.; et al. Breaking the field phenotyping bottleneck in maize with autonomous robots. *Communications biology* **2025**, *8*, 467.
64. Busemeyer, L.; Mentrup, D.; Möller, K.; Wunder, E.; Alheit, K.; Hahn, V.; Maurer, H.P.; Reif, J.C.; Würschum, T.; Müller, J.; et al. BreedVision—A multi-sensor platform for non-destructive field-based phenotyping in plant breeding. *Sensors* **2013**, *13*, 2830–2847.
65. Manish, R.; Lin, Y.C.; Ravi, R.; Hasheminasab, S.M.; Zhou, T.; Habib, A. Development of a miniaturized mobile mapping system for in-row, under-canopy phenotyping. *Remote Sensing* **2021**, *13*, 276.
66. McGuire, M.; Soman, C.; Diers, B.; Chowdhary, G. High throughput soybean pod-counting with in-field robotic data collection and machine-vision based data analysis. *arXiv preprint arXiv:2105.10568* **2021**.
67. Ubbens, J.; Cieslak, M.; Prusinkiewicz, P.; Parkin, I.; Ebersbach, J.; Stavness, I. Latent space phenotyping: automatic image-based phenotyping for treatment studies. *Plant Phenomics* **2020**.
68. Jangra, S.; Chaudhary, V.; Yadav, R.C.; Yadav, N.R. High-throughput phenotyping: a platform to accelerate crop improvement. *Phenomics* **2021**, *1*, 31–53.
69. Wiesner-Hanks, T.; Wu, H.; Stewart, E.; DeChant, C.; Kaczmar, N.; Lipson, H.; Gore, M.A.; Nelson, R.J. Millimeter-level plant disease detection from aerial photographs via deep learning and crowdsourced data. *Frontiers in Plant Science* **2019**, *10*, 1550.
70. Rodriguez-Sanchez, J.; Johnsen, K.; Li, C. A ground mobile robot for autonomous terrestrial laser scanning-based field phenotyping. *arXiv preprint arXiv:2404.04404* **2024**.
71. Grimstad, L.; From, P.J. The Thorvald II agricultural robotic system. *Robotics* **2017**, *6*, 24.
72. Mueller-Sim, T.; Jenkins, M.; Abel, J.; Kantor, G. The Robotanist: A ground-based agricultural robot for high-throughput crop phenotyping. In Proceedings of the 2017 IEEE international conference on robotics and automation (ICRA). IEEE, 2017, pp. 3634–3639.
73. Fasiolo, D.T.; Scalera, L.; Maset, E.; Gasparetto, A. Towards autonomous mapping in agriculture: A review of supportive technologies for ground robotics. *Robotics and Autonomous Systems* **2023**, *169*, 104514.
74. Yang, M.; Li, Z.; Cui, J.; Shao, Y.; Zhai, R.; Qiao, W.; Yang, W.; Song, P. PhenoRob-F: An autonomous ground-based robot for high-throughput phenotyping of field crops. *Plant Phenomics* **2025**, p. 100085.
75. Pugh, N.A.; Thorp, K.R.; Gonzalez, E.M.; Elshikha, D.E.M.; Pauli, D. Comparison of image georeferencing strategies for agricultural applications of small unoccupied aircraft systems. *The Plant Phenome Journal* **2021**, *4*, e20026.
76. Zhang, C.; Lane, B.; Fernández-Campos, M.; Cruz-Sancan, A.; Lee, D.Y.; Gongora-Canul, C.; Ross, T.J.; Da Silva, C.R.; Telenko, D.E.; Goodwin, S.B.; et al. Monitoring tar spot disease in corn at different canopy and temporal levels using aerial multispectral imaging and machine learning. *Frontiers in plant science* **2023**, *13*, 1077403.
77. Gao, M.; Yang, F.; Wei, H.; Liu, X. Individual maize location and height estimation in field from UAV-Borne LiDAR and RGB images. *Remote Sensing* **2022**, *14*, 2292.
78. Che, Y.; Wang, Q.; Xie, Z.; Zhou, L.; Li, S.; Hui, F.; Wang, X.; Li, B.; Ma, Y. Estimation of maize plant height and leaf area index dynamics using an unmanned aerial vehicle with oblique and nadir photography. *Annals of botany* **2020**, *126*, 765–773.
79. Li, Y.; Liang, Z.; Liu, B.; Yin, L.; Wan, F.; Qian, W.; Qiao, X. Applications of 3D Reconstruction Techniques in Crop Canopy Phenotyping: A Review. *Agronomy* **2025**, *15*.
80. Tetila, E.C.; Machado, B.B.; Astolfi, G.; de Souza Belete, N.A.; Amorim, W.P.; Roel, A.R.; Pistori, H. Detection and classification of soybean pests using deep learning with UAV images. *Computers and Electronics in Agriculture* **2020**, *179*, 105836.
81. Chong, Y.L.; Krämer, J.; Chakhvashvili, E.; Marks, E.; Esser, F.; Dreier, A.; Rosu, R.A.; Warstat, K.; Pude, R.; Behnke, S.; et al. The Multi-Sensor and Multi-Temporal Dataset of Multiple Crops for In-Field Phenotyping and Monitoring. *Scientific Data* **2026**.

82. Polk, S.L.; Cui, K.; Plemmons, R.J.; Murphy, J.M. Active diffusion and VCA-assisted image segmentation of hyperspectral images. In Proceedings of the IGARSS 2022-2022 IEEE International Geoscience and Remote Sensing Symposium. IEEE, 2022, pp. 1364–1367.
83. Yue, J.; Feng, H.; Fan, Y.; Liu, Y.; Zhao, C.; Yang, G. Maize phenological stage recognition via coordinated UAV and UGV multi-view sensing and deep learning. *Artificial Intelligence in Agriculture* **2025**.
84. Tan, C.; Sun, J.; Song, H.; Li, C. A customized density map model and segment anything model for cotton boll number, size, and yield prediction in aerial images. *Computers and Electronics in Agriculture* **2025**, 232, 110065.
85. Petti, D.; Li, C.; Chee, P. Real-Time Multi-View Flower Counting With a Ground Mobile Robot. *Journal of Field Robotics* **2025**.
86. Potena, C.; Khanna, R.; Nieto, J.; Siegwart, R.; Nardi, D.; Pretto, A. AgriColMap: Aerial-ground collaborative 3D mapping for precision farming. *IEEE Robotics and Automation Letters* **2019**, 4, 1085–1092.
87. Roldán, J.J.; Garcia-Aunon, P.; Garzón, M.; De León, J.; Del Cerro, J.; Barrientos, A. Heterogeneous multi-robot system for mapping environmental variables of greenhouses. *Sensors* **2016**, 16, 1018.
88. Albiero, D.; Garcia, A.P.; Umezu, C.K.; de Paulo, R.L. Swarm robots in mechanized agricultural operations: A review about challenges for research. *Computers and Electronics in Agriculture* **2022**, 193, 106608.
89. Makondo, N.; Kobo, H.I.; Mathonsi, T.E.; Mamushiane, L. A review on edge computing in 5G-enabled IoT for agricultural applications: Opportunities and challenges. In Proceedings of the 2023 International Conference on Electrical, Computer and Energy Technologies (ICECET). IEEE, 2023, pp. 1–6.
90. Katikaridis, D.; Benos, L.; Kateris, D.; Papageorgiou, E.; Karras, G.; Menexes, I.; Berruto, R.; Sørensen, C.G.; Bochtis, D. Proactive Path Planning Using Centralized UAV-UGV Coordination in Semi-Structured Agricultural Environments. *Applied Sciences* **2026**, 16, 1143.
91. Asiminari, G.; Papazisis, P.; Katikaridis, D.; Kateris, D.; Bochtis, D. Optimized path planning for UGV based on sampling maps. *IEEE Transactions on AgriFood Electronics* **2025**.
92. Mansur, H.; Gadhwal, M.; Abon, J.E.; Flippo, D. Mapping for autonomous navigation of agricultural robots through crop rows using uav. *Agriculture* **2025**, 15, 882.
93. Zhang, Y.; Liu, H.; Shen, Y.; He, S.; Wang, H.; Shen, Y. A systematic review of modeling and control approaches for path tracking in unmanned agricultural ground vehicles. *Agronomy* **2025**, 15, 2274.
94. Wang, R.F.; Xu, M.; Bauer, M.; Schardong, I.; Ma, X.; Chee, P.; Cui, K. Cott-ADNet: Lightweight Real-Time Cotton Boll and Flower Detection Under Field Conditions. In Proceedings of the Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2026, pp. 500–509.
95. Han, S.; Wang, H. Application of Deep Learning Technology in Monitoring Plant Attribute Changes. *Sustainability* **2025**, 17, 7602.
96. Zhang, S.; Zhao, K.; Huo, Y.; Yao, M.; Xue, L.; Wang, H. Mushroom image classification and recognition based on improved ConvNeXt V2. *Journal of Food Science* **2025**, 90, e70133.
97. Wang, Z.; Wang, R.; Wang, M.; Lai, T.; Zhang, M. Self-supervised transformer-based pre-training method with General Plant Infection dataset. In Proceedings of the Chinese Conference on Pattern Recognition and Computer Vision (PRCV). Springer, 2024, pp. 189–202.
98. Volpato, L.; Pinto, F.; González-Pérez, L.; Thompson, I.G.; Borém, A.; Reynolds, M.; Gérard, B.; Molero, G.; Rodrigues Jr, F.A. High throughput field phenotyping for plant height using UAV-based RGB imagery in wheat breeding lines: Feasibility and validation. *Frontiers in Plant Science* **2021**, 12, 591587.
99. Forero, M.G.; Murcia, H.F.; Méndez, D.; Betancourt-Lozano, J. LiDAR platform for acquisition of 3D plant phenotyping database. *Plants* **2022**, 11, 2199.
100. Zhang, L.; Niu, Y.; Zhang, H.; Han, W.; Li, G.; Tang, J.; Peng, X. Maize canopy temperature extracted from UAV thermal and RGB imagery and its application in water stress monitoring. *Frontiers in plant science* **2019**, 10, 1270.
101. Zhao, J.; Gao, A.; Wang, B.; Wen, J.; Duan, Y.; Wang, G.; Li, Z. Modeling and Visualization of Nitrogen and Chlorophyll in Greenhouse Solanum lycopersicum L. Leaves with Hyperspectral Imaging for Nitrogen Stress Diagnosis. *Plants* **2025**, 14, 3276.
102. Łagiewska, M.; Panek-Chwastyk, E. Integrating remote sensing and autonomous robotics in precision agriculture: Current applications and workflow challenges. *Agronomy* **2025**, 15, 2314.
103. Sun, H.; Xi, X.; Wu, A.Q.; Wang, R.F. ToRLNet: A Lightweight Deep Learning Model for Tomato Detection and Quality Assessment Across Ripeness Stages. *Horticulturae* **2025**, 11, 1334.
104. Wang, R.F.; Qin, Y.M.; Zhao, Y.Y.; Xu, M.; Schardong, I.B.; Cui, K. RA-CottNet: A Real-Time High-Precision Deep Learning Model for Cotton Boll and Flower Recognition. *AI* **2025**, 6, 235.

105. Pun Magar, L.; Sandifer, J.; Khatri, D.; Poudel, S.; Kc, S.; Gyawali, B.; Gebremedhin, M.; Chiluwal, A. Plant height measurement using UAV-based aerial RGB and LiDAR images in soybean. *Frontiers in Plant Science* **2025**, *16*, 1488760.
106. Huo, Y.; Wang, R.F.; Zhao, C.T.; Hu, P.; Wang, H. Research on Obtaining Pepper Phenotypic Parameters Based on Improved YOLOX Algorithm. *AgriEngineering* **2025**, *7*, 209.
107. Madec, S.; Baret, F.; De Solan, B.; Thomas, S.; Dutartre, D.; Jezequel, S.; Hemmerlé, M.; Colombeau, G.; Comar, A. High-throughput phenotyping of plant height: comparing unmanned aerial vehicles and ground LiDAR estimates. *Frontiers in plant science* **2017**, *8*, 2002.
108. Fujiwara, R.; Kikawada, T.; Sato, H.; Akiyama, Y. Comparison of remote sensing methods for plant heights in agricultural fields using unmanned aerial vehicle-based structure from motion. *Frontiers in Plant Science* **2022**, *13*, 886804.
109. Tharuka, M.; Kularathna, K.; Ray, R.L. Application of RGB-Imaging techniques for high-throughput plant phenotyping-A Review. *Turkish Journal of Agriculture-Food Science and Technology* **2025**, *13*, 3678–3686.
110. Panigrahi, S.S.; Singh, K.D.; Balasubramanian, P.; Wang, H.; Natarajan, M.; Ravichandran, P. UAV-based LiDAR and multispectral imaging for estimating dry bean plant height, lodging and seed yield. *Sensors* **2025**, *25*, 3535.
111. Husin, N.A.; Khairunniza-Bejo, S.; Abdullah, A.F.; Kassim, M.S.; Ahmad, D.; Azmi, A.N. Application of ground-based LiDAR for analysing oil palm canopy properties on the occurrence of basal stem rot (BSR) disease. *Scientific reports* **2020**, *10*, 6464.
112. Bates, J.S.; Jonard, F.; Bajracharya, R.; Vereecken, H.; Montzka, C. UAS Lidar Derived Metrics for Winter Wheat Biomass Estimations using Multiple Linear Regression. In Proceedings of the IGARSS 2022-2022 IEEE International Geoscience and Remote Sensing Symposium. IEEE, 2022, pp. 7234–7237.
113. Jin, S.; Sun, X.; Wu, F.; Su, Y.; Li, Y.; Song, S.; Xu, K.; Ma, Q.; Baret, F.; Jiang, D.; et al. Lidar sheds new light on plant phenomics for plant breeding and management: Recent advances and future prospects. *ISPRS Journal of Photogrammetry and Remote Sensing* **2021**, *171*, 202–223.
114. Moreno, H.; Andújar, D. Proximal sensing for geometric characterization of vines: A review of the latest advances. *Computers and Electronics in Agriculture* **2023**, *210*, 107901.
115. Tao, S.; Guo, Q.; Xu, S.; Su, Y.; Li, Y.; Wu, F. A geometric method for wood-leaf separation using terrestrial and simulated lidar data. *Photogrammetric Engineering & Remote Sensing* **2015**, *81*, 767–776.
116. Su, Y.; Li, R.; Wang, M.; Li, C.; Ou, M.; Liu, S.; Hou, W.; Wang, Y.; Liu, L. Measurement of Maize Leaf Phenotypic Parameters Based on 3D Point Cloud. *Sensors* **2025**, *25*, 2854.
117. Farhan, S.M.; Yin, J.; Chen, Z.; Memon, M.S. A comprehensive review of LiDAR applications in crop management for precision agriculture. *Sensors* **2024**, *24*, 5409.
118. Tsaris, A.; Lyngaas, I.; Lagergren, J.; Wahib, M.; York, L.; Balaprakash, P.; Lu, D.; Wang, F.; Wang, X. Distributed cross-channel hierarchical aggregation for foundation models. In Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis, 2025, pp. 935–948.
119. Walsh, O.S.; Shafian, S.; Marshall, J.M.; Jackson, C.; McClintick-Chess, J.R.; Blanscet, S.M.; Swoboda, K.; Thompson, C.; Belmont, K.M.; Walsh, W.L. Assessment of UAV based vegetation indices for nitrogen concentration estimation in spring wheat. *Advances in Remote Sensing* **2018**, *7*, 71–90.
120. Li, S.; Cui, Z.; Yang, J.; Wang, B. A review of optical-based three-dimensional reconstruction and multi-source fusion for plant phenotyping. *Sensors* **2025**, *25*, 3401.
121. Nagasubramanian, K.; Jones, S.; Singh, A.K.; Sarkar, S.; Singh, A.; Ganapathysubramanian, B. Plant disease identification using explainable 3D deep learning on hyperspectral images. *Plant methods* **2019**, *15*, 98.
122. Nguyen, C.; Sagan, V.; Maimaitiyiming, M.; Maimaitijiang, M.; Bhadra, S.; Kwasniewski, M.T. Early detection of plant viral disease using hyperspectral imaging and deep learning. *Sensors* **2021**, *21*, 742.
123. Polk, S.L.; Cui, K.; Chan, A.H.; Coomes, D.A.; Plemmons, R.J.; Murphy, J.M. Unsupervised diffusion and volume maximization-based clustering of hyperspectral images. *Remote Sensing* **2023**, *15*, 1053.
124. Polk, S.L.; Chan, A.H.; Cui, K.; Plemmons, R.J.; Coomes, D.A.; Murphy, J.M. Unsupervised detection of ash dieback disease (*Hymenoscyphus fraxineus*) using diffusion-based hyperspectral image clustering. In Proceedings of the IGARSS 2022-2022 IEEE International Geoscience and Remote Sensing Symposium. IEEE, 2022, pp. 2287–2290.
125. Brown, M.T.; Oh, S.; Rainey, K.M.; Telenko, D.E. Presymptomatic leaf reflectance of fusarium virguliforme-infected soybean plants in greenhouse conditions. *PhytoFrontiers™* **2024**, *4*, 544–552.

126. Pintus, M.; Colucci, F.; Maggio, F. Emerging developments in real-time edge aiot for agricultural image classification. *IoT* **2025**, *6*, 13.
127. Cui, K.; Plemmons, R.J. Unsupervised classification of AVIRIS-NG hyperspectral images. In Proceedings of the 2021 11th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS). IEEE, 2021, pp. 1–5.
128. Cao, Z.; Lu, Y.; Yuan, J.; Xin, H.; Wang, R.; Nie, F. Tensorized Graph Learning for Spectral Ensemble Clustering. *IEEE Transactions on Circuits and Systems for Video Technology* **2025**, *35*, 2662–2674.
129. Pineda, M.; Barón, M.; Pérez-Bueno, M.L. Thermal imaging for plant stress detection and phenotyping. *Remote Sensing* **2020**, *13*, 68.
130. Faqeerzada, M.A.; Park, E.; Lim, J.; Kim, K.; Sathasivam, R.; Park, S.U.; Kim, H.; Cho, B.K. Development of multi-sensing technologies for high-throughput morphological, physiological, and biochemical phenotyping of drought-stressed watermelon plants. *Plant Physiology and Biochemistry* **2025**, p. 110577.
131. Cao, Z.; Xin, H.; Wang, R.; Nie, F. Superpixel-Based Bipartite Graph Clustering Enriched with Spatial Information for Hyperspectral and LiDAR Data. *IEEE Transactions on Geoscience and Remote Sensing* **2025**, *63*, 1–15.
132. Zhou, H.; Wang, J.; Chen, Y.; Hu, L.; Li, Z.; Xie, F.; He, J.; Wang, P. Neural network-based SLAM/GNSS fusion localization algorithm for agricultural robots in orchard GNSS-degraded or denied environments. *Agriculture* **2025**, *15*, 1612.
133. Wu, H.; Wang, X.; Chen, X.; Zhang, Y.; Zhang, Y. Review on key technologies for autonomous navigation in field agricultural machinery. *Agriculture* **2025**, *15*, 1297.
134. Qu, J.; Gu, Y.; Qiu, Z.; Guo, K.; Zhu, Q. Development of an Orchard Inspection Robot: A ROS-Based LiDAR-SLAM System with Hybrid A*-DWA Navigation. *Sensors* **2025**, *25*, 6662.
135. Cao, Z.; Lu, Y.; Xin, H.; Yu, C.; Wang, R.; Nie, F. Spatial-Spectral Bipartite Graph Clustering with Low-Frequency Tensor Regularization for Hyperspectral and LiDAR Data. *IEEE Transactions on Geoscience and Remote Sensing* **2025**, *63*, 1–17. <https://doi.org/10.1109/TGRS.2025.3622499>.
136. Schmidt, F.; Blessing, C.; Enzweiler, M.; Valada, A. Visual-Inertial SLAM for Unstructured Outdoor Environments: Benchmarking the Benefits and Computational Costs of Loop Closing. *Journal of Field Robotics* **2025**, *42*, 3726–3747.
137. Shi, Z.; Bai, Z.; Yi, K.; Qiu, B.; Dong, X.; Wang, Q.; Jiang, C.; Zhang, X.; Huang, X. Vision and 2D LiDAR fusion-based navigation line extraction for autonomous agricultural robots in dense pomegranate orchards. *Sensors* **2025**, *25*, 5432.
138. Mineiro, A.L.; Affonso, F.; Becker, M. End-to-End Crop Row Navigation via LiDAR-Based Deep Reinforcement Learning. In Proceedings of the 2025 IEEE International Conference on Advanced Robotics (ICAR). IEEE, 2025, pp. 811–817.
139. Qadri, M.; Freeman, H.; Schneider, E.; Kantor, G. Toward Semantic Scene Understanding for Fine-Grained 3D Modeling of Plants. *arXiv preprint arXiv:2312.17110* **2023**.
140. Zhang, W.; Huang, Q.; Ma, M.; Jiang, Y.; Chen, Y.; Huang, Z.; Wu, W.; Cui, K.; Lian, R.; Wu, Z.; et al. Center-guided Classifier for Semantic Segmentation of Remote Sensing Images. *IEEE Transactions on Geoscience and Remote Sensing* **2026**.
141. Rapado-Rincon, D.; Kootstra, G. Tree-SLAM: semantic object SLAM for efficient mapping of individual trees in orchards. *Smart Agricultural Technology* **2025**, p. 101439.
142. Pan, Y.; Hu, K.; Cao, H.; Kang, H.; Wang, X. A novel perception and semantic mapping method for robot autonomy in orchards. *Computers and Electronics in Agriculture* **2024**, *219*, 108769.
143. Zheng, Y.; Liu, A.; Huang, A.; Kim, D.H.; Shen, Y.; Lee, K.H. Realtime multi-RGBD SLAM framework for 3D reconstruction and phenotyping in large-scale apple orchards. *Computers and Electronics in Agriculture* **2026**, *240*, 111170.
144. Li, X.; Su, J.; Yue, Z.; Duan, F. Adaptive multi-ROI agricultural robot navigation line extraction based on image semantic segmentation. *Sensors* **2022**, *22*, 7707.
145. Yan, Z.; Wang, M.J.S.; et al. MFE-DETR: Multimodal Feature-Enhanced Detection Transformer for RGB-Infrared Object Detection in Aerial Imagery. *Symmetry* **2026**.
146. Shu, K.L.; Wang, M.J.S. Multi-Domain Feature Fusion Transformer with Cross-Domain Robustness for Facial Expression Recognition. *Symmetry* (20738994) **2026**, *18*.
147. Wang, H.; Wang, M. Subject-Independent Multimodal Interaction Modeling for Joint Emotion and Immersion Estimation in Virtual Reality. *Symmetry* **2026**, *18*, 451.

148. Wei, Z.L.; An, H.Y.; Yao, Y.; Su, W.C.; Li, G.; Saifullah.; Sun, B.F.; Wang, M.J.S. FSTGAT: Financial Spatio-Temporal Graph Attention Network for Non-Stationary Financial Systems and Its Application in Stock Price Prediction. *Symmetry* **2025**, *17*, 1344.
149. Huang, Y.; Xu, S.; Chen, H.; Li, G.; Dong, H.; Yu, J.; Zhang, X.; Chen, R. A review of visual perception technology for intelligent fruit harvesting robots. *Frontiers in Plant Science* **2025**, *16*, 1646871.
150. Pan, S.; Huang, X.; Bennewitz, M. Temporal-Prior-Guided View Planning for Periodic 3D Plant Reconstruction. *arXiv preprint arXiv:2510.07028* **2025**.
151. Wang, Y.; Chen, Y.; Wang, D. Recognition of multi-modal fusion images with irregular interference. *PeerJ Computer Science* **2022**, *8*, e1018.
152. Yang, Z.X.; Li, Y.; Wang, R.F.; Hu, P.; Su, W.H. Deep learning in multimodal fusion for sustainable plant care: A comprehensive review. *Sustainability* **2025**, *17*, 5255.
153. Yao, M.; Huo, Y.; Ran, Y.; Tian, Q.; Wang, R.; Wang, H. Neural radiance field-based visual rendering: A comprehensive review. *arXiv preprint arXiv:2404.00714* **2024**.
154. Chopra, S.; Cladera, F.; Murali, V.; Kumar, V. Agrinerf: Neural radiance fields for agriculture in challenging lighting conditions. *arXiv preprint arXiv:2409.15487* **2024**.
155. Li, A.; Wang, C.; Wang, A.; Sun, J.; Gu, F.; Zhang, T. YOLO-MSRF: A Multimodal Segmentation and Refinement Framework for Tomato Fruit Detection and Segmentation with Count and Size Estimation Under Complex Illumination. *Agriculture* **2026**, *16*, 277.
156. Huang, Y.; Lyu, B.; Gao, T.; Wu, X.; Duan, Y. CornMFN: A Multimodal Fusion Network for Corn Phenology Stage Identification. *Smart Agricultural Technology* **2025**, p. 101202.
157. Kim, S.; Xin, X.; Kim, S.Y.; Kim, G.; Baek, M.g.; Won, D.Y.; Baek, C.H.; Kim, G. De-occlusion models and diffusion-based data augmentation for size estimation of on-plant oriental melons. *Plant Phenomics* **2025**, p. 100097.
158. Yang, J.; Deng, H.; Zhang, Y.; Zhou, Y.; Miao, T. Application of amodal segmentation for shape reconstruction and occlusion recovery in occluded tomatoes. *Frontiers in Plant Science* **2024**, *15*, 1376138.
159. Jiang, K.; Guo, W.; Zhang, W. Amodal Segmentation and Trait Extraction of On-Branch Soybean Pods with a Synthetic Dual-Mask Dataset. *Sensors* **2025**, *25*, 6486.
160. He, L.; Sun, Y.; Chen, L.; Feng, Q.; Li, Y.; Lin, J.; Qiao, Y.; Zhao, C. Advance on agricultural robot Hand-Eye coordination for agronomic task: A review. *Engineering* **2025**.
161. Yao, M.; Huo, Y.; Tian, Q.; Zhao, J.; Liu, X.; Wang, R.; Xue, L.; Wang, H. FMRFT: Fusion mamba and DETR for query time sequence intersection fish tracking. *Computers and Electronics in Agriculture* **2025**, *237*, 110742.
162. Chen, Y.; Mao, J.; Wang, R.F. Joint Learning of Emotion and Singing Style for Enhanced Music Style Understanding. *Sensors* **2025**, *25*, 7575.
163. Wang, R.F.; Su, W.H. The application of deep learning in the whole potato production Chain: A Comprehensive review. *Agriculture* **2024**, *14*, 1225.
164. Huo, Y.; Meng, X.; Zhang, L.; Jiang, H.; Zhong, Y.; Yao, M.; Wang, H. Diff-Art: Category-level Articulation Pose Estimation via Conditional Diffusion. In Proceedings of the 2025 IEEE International Conference on Multimedia and Expo (ICME). IEEE, 2025, pp. 1–6.
165. Wu, A.Q.; Li, K.L.; Song, Z.Y.; Lou, X.; Hu, P.; Yang, W.; Wang, R.F. Deep learning for sustainable aquaculture: Opportunities and challenges. *Sustainability* **2025**, *17*, 5084.
166. Han, J.; Li, W.; Xia, W.; Wang, F. Research on complete coverage path planning of agricultural robots based on Markov chain improved genetic algorithm. *Applied Sciences* **2024**, *14*, 9868.
167. Han, C.; Wu, W.; Luo, X.; Li, J. Visual navigation and obstacle avoidance control for agricultural robots via LiDAR and camera. *Remote sensing* **2023**, *15*, 5402.
168. Ma, R.; Fuentes, A.; Yoon, S.; Lee, W.Y.; Kim, S.C.; Kim, H.; Park, D.S. Local refinement mechanism for improved plant leaf segmentation in cluttered backgrounds. *Frontiers in plant science* **2023**, *14*, 1211075.
169. Schunck, D.; Magistri, F.; Rosu, R.A.; Cornelißen, A.; Chebrolu, N.; Paulus, S.; Léon, J.; Behnke, S.; Stachniss, C.; Kuhlmann, H.; et al. Pheno4D: A spatio-temporal dataset of maize and tomato plant point clouds for phenotyping and advanced plant analysis. *Plos one* **2021**, *16*, e0256340.
170. El Amraoui, K.; El Ansari, M.; Lghoul, M.; El Alaoui, M.; Abanay, A.; Jabri, B.; Masmoudi, L.; Valente de Oliveira, J. Embedding a real-time strawberry detection model into a pesticide-spraying mobile robot for greenhouse operation. *Applied Sciences* **2024**, *14*, 7195.
171. Chebrolu, N.; Magistri, F.; Läbe, T.; Stachniss, C. Registration of spatio-temporal point clouds of plants for phenotyping. *PloS one* **2021**, *16*, e0247243.

172. Mier, G.; Vélez, S.; Valente, J.; de Bruin, S. Soil2Cover: Coverage path planning minimizing soil compaction for sustainable agriculture. *Precision Agriculture* **2025**, *26*, 57.
173. Wang, M.J.S.; Yuan, J.; Lin, S.W. Ordered and Hamilton Digraphs. *Chinese Quarterly Journal of Mathematics* **2010**, *25*, 317–326.
174. Wang, S.; Wangmu, J.; Qi, Z.; Ren, Y. Embedding paths into the 4-ary n-cube with faulty nodes. In Proceedings of the 2011 International Conference on Consumer Electronics, Communications and Networks (CECNet). IEEE, 2011, pp. 4949–4951.
175. Bochtis, D.; Vougioukas, S. Minimising the non-working distance travelled by machines operating in a headland field pattern. *Biosystems engineering* **2008**, *101*, 1–12.
176. Fan, Y.; Feixiang, L.; Longfei, C.; Han, S.; Jingxing, G.; Junzhe, Q.; Xinyu, X. Application of Navigation Path Planning and Trajectory Tracking Control Methods for Agricultural Robots. *Agriculture* **2025**, *16*, 64.
177. Yang, C.; Zheng, D.; Chen, S.; Mansurova, M.; Belgibaev, B.; Zhao, B. AgriPath: a robust multi-objective path planning framework for agricultural robots in dynamic field environments. *Frontiers in Plant Science* **2025**, *16*, 1687747.
178. Vahdanjoo, M.; Gislum, R.; Sørensen, C.A.G. Three-dimensional area coverage planning model for robotic application. *Computers and Electronics in Agriculture* **2024**, *219*, 108789.
179. Chen, J.; Qiang, H.; Wu, J.; Xu, G.; Wang, Z. Navigation path extraction for greenhouse cucumber-picking robots using the prediction-point Hough transform. *Computers and Electronics in Agriculture* **2021**, *180*, 105911.
180. Chen, J.; Qiang, H.; Wu, J.; Xu, G.; Wang, Z.; Liu, X. Extracting the navigation path of a tomato-cucumber greenhouse robot based on a median point Hough transform. *Computers and Electronics in Agriculture* **2020**, *174*, 105472.
181. Sun, Q.; Diao, M.; Li, Y.; Zhang, Y. An improved binocular visual odometry algorithm based on the random sample consensus in visual navigation systems. *Industrial Robot: An International Journal* **2017**, *44*, 542–551.
182. Zhou, M.; Xia, J.; Yang, F.; Zheng, K.; Hu, M.; Li, D.; Zhang, S. Design and experiment of visual navigated UGV for orchard based on Hough matrix and RANSAC. *International Journal of Agricultural and Biological Engineering* **2021**, *14*, 176–184.
183. Ma, Z.; Wang, X.; Chen, X.; Hu, B.; Li, J. Advances in Crop Row Detection for Agricultural Robots: Methods, Performance Indicators, and Scene Adaptability. *Agriculture* **2025**, *15*, 2151.
184. Ammann, N.; Andert, F. Visual navigation for autonomous, precise and safe landing on celestial bodies using unscented kalman filtering. In Proceedings of the 2017 IEEE Aerospace Conference. IEEE, 2017, pp. 1–12.
185. Chen, S.Y. Kalman filter for robot vision: a survey. *IEEE Transactions on industrial electronics* **2011**, *59*, 4409–4420.
186. Wu, T.; Liu, D.; Li, X. Designing Hybrid Mobility for Agricultural Robots: Performance Analysis of Wheeled and Tracked Systems in Variable Terrain. *Machines* **2025**, *13*, 572.
187. Tu, Y.H.; Wang, R.F.; Su, W.H. Active disturbance rejection control—New trends in agricultural cybernetics in the future: A comprehensive review. *Machines* **2025**, *13*, 111.
188. Chen, Z.; Yin, J.; Farhan, S.M.; Liu, L.; Zhang, D.; Zhou, M.; Cheng, J. A comprehensive review of obstacle avoidance for autonomous agricultural machinery in multi-operational environment. *Artificial Intelligence in Agriculture* **2025**.
189. Chakraborty, S.; Elangovan, D.; Govindarajan, P.L.; ELnaggar, M.F.; Alrashed, M.M.; Kamel, S. A comprehensive review of path planning for agricultural ground robots. *Sustainability* **2022**, *14*, 9156.
190. Yao, X.; Zhang, B.; Wang, X.; Su, Y.; Cao, G.; Bian, Y. Adaptive navigation for robots in unstructured agricultural environments using stable feature localization and multi-sensor obstacle detection. *Computers and Electronics in Agriculture* **2025**, *234*, 110302.
191. Zhu, R.; Cui, K.; Tang, W.; Wang, R.F.; Alqahtani, S.; Lutz, D.; Yang, F.; Fine, P.; Karubian, J.; Plemmons, R.; et al. From Orthomosaics to Raw UAV Imagery: Enhancing Palm Detection and Crown-Center Localization. *arXiv preprint arXiv:2509.12400* **2025**.
192. Sapkota, R.; Cheppally, R.H.; Sharda, A.; Karkee, M. YOLO26: key architectural enhancements and performance benchmarking for real-time object detection. *arXiv preprint arXiv:2509.25164* **2025**.
193. Wang, R.F.; Tu, Y.H.; Chen, Z.Q.; Zhao, C.T.; Su, W.H. A Lettpoint-Yolov11l Based Intelligent Robot for Precision Intra-Row Weeds Control in Lettuce. *Available at SSRN 5162748* **2025**.
194. Tian, Q.; Huo, Y.; Yao, M.; Wang, H. A method for detecting dead fish on large water surfaces based on improved YOLOv10. *arXiv preprint arXiv:2409.00388* **2024**.

195. Han, Y.S.; Zhao, S.L.; Chen, C.; Cui, K.; Hu, P.; Wang, R.F. SEAF-Net: A Sustainable and Lightweight Attention-Enhanced Detection Network for Underwater Fish Species Recognition. *Journal of Marine Science and Engineering* **2026**, *14*, 351.
196. Gai, R.; Chen, N.; Yuan, H. A detection algorithm for cherry fruits based on the improved YOLO-v4 model. *Neural computing and applications* **2023**, *35*, 13895–13906.
197. Mirhaji, H.; Soleymani, M.; Asakereh, A.; Mehdizadeh, S.A. Fruit detection and load estimation of an orange orchard using the YOLO models through simple approaches in different imaging and illumination conditions. *Computers and Electronics in Agriculture* **2021**, *191*, 106533.
198. Bai, Y.; Yu, J.; Yang, S.; Ning, J. An improved YOLO algorithm for detecting flowers and fruits on strawberry seedlings. *Biosystems Engineering* **2024**, *237*, 1–12.
199. Wang, J.; Gao, Z.; Zhang, Y.; Zhou, J.; Wu, J.; Li, P. Real-time detection and location of potted flowers based on a ZED camera and a YOLO V4-tiny deep learning algorithm. *Horticulturae* **2021**, *8*, 21.
200. Sun, H.; Wang, R.F. BMDNet-YOLO: A Lightweight and Robust Model for High-Precision Real-Time Recognition of Blueberry Maturity. *Horticulturae* **2025**, *11*, 1202.
201. Han, Y.; Duan, B.; Guan, R.; Yang, G.; Zhen, Z. LUFFD-YOLO: A lightweight model for UAV remote sensing forest fire detection based on attention mechanism and multi-level feature fusion. *Remote Sensing* **2024**, *16*, 2177.
202. Pan, F.; Wu, Y.; Cui, K.; Chen, S.; Li, Y.; Liu, Y.; Shakoor, A.; Zhao, H.; Lu, B.; Zhi, S.; et al. Accurate detection and instance segmentation of unstained living adherent cells in differential interference contrast images. *Computers in Biology and Medicine* **2024**, *182*, 109151.
203. Liu, S.; Xue, J.; Zhang, T.; Lv, P.; Qin, H.; Zhao, T. Research progress and prospect of key technologies of fruit target recognition for robotic fruit picking. *Frontiers in Plant Science* **2024**, *15*, 1423338.
204. He, K.; Gkioxari, G.; Dollár, P.; Girshick, R. Mask r-cnn. In Proceedings of the Proceedings of the IEEE international conference on computer vision, 2017, pp. 2961–2969.
205. Ni, X.; Li, C.; Jiang, H.; Takeda, F. Deep learning image segmentation and extraction of blueberry fruit traits associated with harvestability and yield. *Horticulture research* **2020**, *7*.
206. Tang, W.; Cui, K.; Chan, R.H. Optimized hard exudate detection with supervised contrastive learning. In Proceedings of the 2024 IEEE International Symposium on Biomedical Imaging (ISBI). IEEE, 2024, pp. 1–5.
207. Barreto, A.; Reifenrath, L.; Vogg, R.; Sinz, F.; Mahlein, A.K. Data augmentation for mask-based leaf segmentation of UAV-images as a basis to extract leaf-based phenotyping parameters. *KI-Künstliche Intelligenz* **2023**, *37*, 143–156.
208. Zhou, G.; Li, L.; Chen, X. Advances in Artificial Intelligence for Plant Research. *Plants* **2026**, *15*, 142.
209. Zhang, T.; Huang, J.; Niu, J.; Liu, Z.; Zhang, L.; Song, H. Occlusion Avoidance for Harvesting Robots: A Lightweight Active Perception Model. *Sensors (Basel, Switzerland)* **2026**, *26*, 291.
210. Cheng, G.; Gu, C. Enhancing point cloud classification and segmentation with attention-enhanced SO-PointNet++. *IEEE Access* **2024**, *12*, 195986–195995.
211. He, Q.; Peng, J.; Jiang, Z.; Hu, X.; Zhang, J. Pointseg: A training-free paradigm for 3d scene segmentation via foundation models. In Proceedings of the Proceedings of the IEEE/CVF International Conference on Computer Vision, 2025, pp. 2657–2667.
212. Zhao, Y.; Liu, D.; Wang, Z.; Yao, J.; Yu, J.; Wang, Z.; Jia, Z. Automated Phenotyping of Maize from 3D Point Clouds Using an Optimized Deep Learning Approach. *Agriculture* **2025**, *15*, 2430.
213. Qiao, G.; Zhang, Z.; Niu, B.; Han, S.; Yang, E. Plant stem and leaf segmentation and phenotypic parameter extraction using neural radiance fields and lightweight point cloud segmentation networks. *Frontiers in Plant Science* **2025**, *16*, 1491170.
214. Cui, K.; Li, R.; Polk, S.L.; Murphy, J.M.; Plemmons, R.J.; Chan, R.H. Unsupervised spatial-spectral hyperspectral image reconstruction and clustering with diffusion geometry. *arXiv preprint arXiv:2204.13497* **2022**.
215. Yang, S.; Cui, K.; Jia, Y.; Ding, Y.; Guan, R.; Ding, Y. Superpixel-Level Hypergraph Regularized Multi-View Clustering for Hyperspectral Images. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* **2026**, pp. 1–16. <https://doi.org/10.1109/JSTARS.2026.3673839>.
216. Marks, E.A.; Nunes, L.; Magistri, F.; Sodano, M.; Marcuzzi, R.; Zimmermann, L.; Behley, J.; Stachniss, C. Tree Skeletonization from 3D Point Clouds by Denoising Diffusion. In Proceedings of the Proceedings of the IEEE/CVF International Conference on Computer Vision, 2025, pp. 27607–27617.

217. Meyer, L.; Gilson, A.; Scholz, O.; Stamminger, M. CherryPicker: Semantic skeletonization and topological reconstruction of cherry trees. In Proceedings of the Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2023, pp. 6244–6253.
218. He, T.; Li, M.; Jin, D. Deep learning-based time series prediction for precision field crop protection. *Frontiers in Plant Science* **2025**, *16*, 1575796.
219. Wang, Y.; Jiang, T.; Shao, Z.; Ye, H.; Sun, J.; Ma, M.; Wang, Q.; Zhang, J.; Chen, Y.; Li, H.H. Accelerating Denoising Generative Models is as Easy as Predicting Second-Order Difference, 2026.
220. Qin, Y.M.; Tu, Y.H.; Li, T.; Ni, Y.; Wang, R.F.; Wang, H. Deep Learning for sustainable agriculture: A systematic review on applications in lettuce cultivation. *Sustainability* **2025**, *17*, 3190.
221. Carraro, A.; Sozzi, M.; Marinello, F. The Segment Anything Model (SAM) for accelerating the smart farming revolution. *Smart agricultural technology* **2023**, *6*, 100367.
222. Wang, X.; Xing, X.; Qiao, X.; Yang, Y.; Zhang, K.; Liu, Y.; Yang, Y.; Yang, Y.; Luo, B.; Ji, T.; et al. Automatic Annotation and Performance Evaluation of Orchard Pear Fruit Using SAM-Based Zero-Shot Segmentation. *Smart Agricultural Technology* **2026**, p. 101826.
223. Madadam, H.; Nasir, F.E.; Haruehansapong, K. Optimizing watermelon leaf disease detection using Sam-based augmentation with YOLO for practical agricultural solutions. *Smart Agricultural Technology* **2025**, p. 101326.
224. Paul, S.; Das, S.; Khan, M.R.; Srivastava, A.; Nebapure, S.; Roy, A.; Sinha, P. YOLOv9t-DyE: A Lightweight Detection Framework with SAM-Assisted Segmentation for Quantifying Chilli Leaf Curl Complex. *Smart Agricultural Technology* **2025**, p. 101764.
225. Al Nahian, M.J.; Ghosh, T.; Sheikhi, F.; McQuillan, I.; Maleki, F. WheatSAM: A Two-Stage Wheat Head Automatic Segmentation Framework. In Proceedings of the Proceedings of the Conference on Robots and Vision. PubPub, 2025.
226. Hua, S.; Yang, B.; Zhang, X.; Qi, J.; Su, F.; Sun, J.; Ruan, Y. GDPGO-SAM: an unsupervised fine segmentation of desert vegetation driven by grounding DINO prompt generation and optimization segment anything model. *Remote Sensing* **2025**, *17*, 691.
227. Muhammad, A.; Salman, Z.; Lee, K.; Han, D. Harnessing the power of diffusion models for plant disease image augmentation. *Frontiers in plant science* **2023**, *14*, 1280496.
228. Roggiolani, G.; Bailey, B.N.; Behley, J.; Stachniss, C. Generation of labeled leaf point clouds for plants trait estimation. *Plant Phenomics* **2025**, p. 100071.
229. Renkai, D.; Xiangyuan, Q.; Xiangpeng, M.; Chen, X.; Zhang, L.; Yixin, M.; Li, A.; Qing, Y. A Review on the Chassis Configurations and Key Technologies of Agricultural Robots. *Agriculture* **2025**, *15*, 2379.
230. Zhang, Y.; Shen, Y.; Liu, H.; He, S.; Khan, Z. A composite sliding mode controller with extended disturbance observer for 4WSS agricultural robots in unstructured farmlands. *Computers and Electronics in Agriculture* **2025**, *232*, 110069.
231. Anastasiou, E.; Ntakos, G.; Kanakari, E.; Bitsika, S.; Gemtou, M.; Katsaragakis, M.; Soudris, D.; Volioti, C.; Arvanitou, E.M.; Folina, M.T.; et al. Applications of Robotics and Extended Reality in Agriculture: A review. *Smart Agricultural Technology* **2025**, p. 101521.
232. Fontani, M.; Luglio, S.M.; Gagliardi, L.; Peruzzi, A.; Frascioni, C.; Raffaelli, M.; Fontanelli, M. A systematic review of 59 field robots for agricultural tasks: applications, trends, and future directions. *Agronomy* **2025**, *15*, 2185.
233. Hernández, H.A.; Mondragón, I.F.; González, S.R.; Pedraza, L.F. Reconfigurable agricultural robotics: Control strategies, communication, and applications. *Computers and Electronics in Agriculture* **2025**, *234*, 110161.
234. Zhang, Z.; He, W.; Wu, F.; Quesada, L.; Xiang, L. Development of a bionic hexapod robot with adaptive gait and clearance for enhanced agricultural field scouting. *Frontiers in Robotics and AI* **2024**, *11*, 1426269.
235. Martelli, S.; Martini, V.; Mocera, F.; Soma', A. Co-Simulation Model of an Autonomous Driving Rover for Agricultural Applications. *Robotics* **2025**, *14*, 120.
236. Yao, S.; Pan, S.; Bennewitz, M.; Hauser, K. Safe leaf manipulation for accurate shape and pose estimation of occluded fruits. In Proceedings of the 2025 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2025, pp. 16795–16802.
237. Zhang, S.; Liu, T.; Li, X.; Cai, C.; Chang, C.; Xue, X. Key Technologies of Robotic Arms in Unmanned Greenhouse. *Agronomy* **2025**, *15*, 2498.
238. Russo, M.; Santoro, C.; Santoro, F.F.; Tudisco, A. Autonomous Robotic Platform for Precision Viticulture: Integrated Mobility, Multimodal Sensing, and AI-Based Leaf Sampling. In Proceedings of the Actuators. MDPI, 2026, Vol. 15, p. 91.

239. Li, X.; Chen, Z.; Uppuluri, R.S.; Zhou, P.; Zhao, T.; Good, D.Z.; She, Y.; Jin, J. Robotic system with tactile-enabled leaf tracking for high-resolution hyperspectral imaging device for autonomous corn leaf phenotyping in controlled environments. *Smart Agricultural Technology* **2025**, p. 101427.
240. Zhao, C.T.; Wang, R.F.; Tu, Y.H.; Pang, X.X.; Su, W.H. Automatic lettuce weed detection and classification based on optimized convolutional neural networks for robotic weed control. *Agronomy* **2024**, *14*, 2838.
241. Shao, Z.; Wang, Y.; Wang, Q.; Jiang, T.; Du, Z.; Ye, H.; Zhuo, D.; Chen, Y.; Li, H. Flashsvd: Memory-efficient inference with streaming for low-rank models. *arXiv preprint arXiv:2508.01506* **2025**.
242. Aljami, H.M.; Alrowais, N.A.; AlAwajy, A.M.; Alhrgan, S.O.; Aldwaani, R.A.; Alsawadi, M.S.; Saqib, N.U.; Alam, S.S.; Alsubaie, R. Benchmarking YOLOv8 Variants for Object Detection Efficiency on Jetson Orin NX for Edge Computing Applications. *Computers* **2026**, *15*, 74.
243. Shuai, Y.; Shi, J.; Li, Y.; Zhou, S.; Zhang, L.; Mu, J. YOLO-SW: A Real-Time Weed Detection Model for Soybean Fields Using Swin Transformer and RT-DETR. *Agronomy* **2025**, *15*, 1712.
244. Yang, Z.; Khan, Z.; Shen, Y.; Liu, H. GTDR-YOLOv12: optimizing YOLO for efficient and accurate weed detection in agriculture. *Agronomy* **2025**, *15*, 1824.
245. Qi, Z.; Wang, J.; Yang, G.; Wang, Y. Lightweight YOLOv8-Based Model for Weed Detection in Dryland Spring Wheat Fields. *Sustainability* **2025**, *17*, 6150.
246. Spagnuolo, M.; Todde, G.; Caria, M.; Furnitto, N.; Schillaci, G.; Failla, S. Agricultural robotics: A technical review addressing challenges in sustainable crop production. *Robotics* **2025**, *14*, 9.
247. Maulana, D.; Ramasamy, R.K. Systematic Review of Quantization-Optimized Lightweight Transformer Architectures for Real-Time Fruit Ripeness Detection on Edge Devices. *Computers* **2026**, *15*, 69.
248. Surantha, N.; Sutisna, N. Key considerations for real-time object recognition on edge computing devices. *Applied Sciences* **2025**, *15*, 7533.
249. Wu, D.; Lv, S.; Jiang, M.; Song, H. Using channel pruning-based YOLO v4 deep learning algorithm for the real-time and accurate detection of apple flowers in natural environments. *Computers and Electronics in Agriculture* **2020**, *178*, 105742.
250. Xu, W.; Su, Q.; Ji, T.; Sun, H.; Chen, W.; Ji, C.; Wang, T. Real-time pest monitoring with RSCDet: Deploying a novel lightweight detection model on embedded systems. *Smart Agricultural Technology* **2025**, p. 101280.
251. Tonmoy, M.R.; Hossain, M.M.; Dey, N.; Mridha, M.F. MobilePlantViT: a Mobile-friendly hybrid ViT for generalized plant disease image classification. *arXiv preprint arXiv:2503.16628* **2025**.
252. Gauttam, H.; Chauhan, V.; Pattanaik, K.; Trivedi, A.; Ghosh, H.; et al. A comprehensive review of Edge Computing empowered smart agriculture: Trends, Opportunities and Future directions. *Computers and Electronics in Agriculture* **2026**, *241*, 111252.
253. Shamshiri, R.R.; Weltzien, C.; Hameed, I.A.; Yule, I.J.; Grift, T.E.; Balasundram, S.K.; Pitonakova, L.; Ahmad, D.; Chowdhary, G. Research and development in agricultural robotics: A perspective of digital farming. *International Journal of Agricultural and Biological Engineering* **2018**, *11*, 1–14.
254. Friha, O.; Ferrag, M.A.; Shu, L.; Maglaras, L.; Wang, X. Internet of things for the future of smart agriculture: A comprehensive survey of emerging technologies. *IEEE/CAA Journal of Automatica Sinica* **2021**, *8*, 718–752.
255. Vresk, T.; Čavrak, I. Architecture of an interoperable IoT platform based on microservices. In Proceedings of the 2016 39th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO). IEEE, 2016, pp. 1196–1201.
256. Ullah, M.; Ali, N.; Nadeem, N.; Bais, A. AgMIC: Agricultural Masked Image Consistency for Cross-Domain Segmentation. In Proceedings of the Proceedings of the IEEE/CVF International Conference on Computer Vision, 2025, pp. 7080–7090.
257. Hu, X.; Chen, S.; Duan, Q.; Ahn, C.K.; Shang, H.; Zhang, D. Domain Adaptation for Big Data in Agricultural Image Analysis: A Comprehensive Review. *arXiv preprint arXiv:2506.05972* **2025**.
258. Cui, K.; Shao, Z.; Larsen, G.; Pauca, V.; Alqahtani, S.; Segurado, D.; Pinheiro, J.; Wang, M.; Lutz, D.; Plemmons, R.; et al. Palmprobnet: A probabilistic approach to understanding palm distributions in ecuadorian tropical forest via transfer learning. In Proceedings of the Proceedings of the 2024 ACM Southeast Conference, 2024, pp. 272–277.
259. Oehme, L.H.; Boysen, J.; Wu, Z.; Stein, A.; Müller, J. Orchestrating segment anything models to accelerate segmentation annotation on agricultural image datasets. *Frontiers in Artificial Intelligence* **2026**, *8*, 1748468.
260. Zhang, H.W.; Wang, R.F.; Wang, Z.; Su, W.H. DLCPD-25: A Large-Scale and Diverse Dataset for Crop Disease and Pest Recognition. *Sensors* **2025**, *25*, 7098.
261. Coleman, G.R.; Salter, W.T. More eyes on the prize: open-source data, software and hardware for advancing plant science through collaboration. *AoB Plants* **2023**, *15*, plad010.

262. Hartley, Z.K.; Lind, R.J.; Pound, M.P.; French, A.P. Domain targeted synthetic plant style transfer using stable diffusion LoRA and ControlNet. In Proceedings of the Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2024, pp. 5375–5383.
263. Wang, M.; Yang, W.; Wang, S. Conditional matching preclusion number for the Cayley graph on the symmetric group. *Acta Math. Appl. Sin.(Chinese Series)* **2013**, *36*, 813–820.
264. Wang, S.; Wang, M. The Edge Connectivity of Expanded k-Ary n-Cubes. *Discrete Dynamics in Nature and Society* **2018**, *2018*, 7867342.
265. Wang, S.; Wang, M. A Note on the Connectivity of m-Ary n-Dimensional Hypercubes. *Parallel Processing Letters* **2019**, *29*, 1950017.
266. Wang, M.; Xu, S.; Jiang, J.; Xiang, D.; Hsieh, S.Y. Global reliable diagnosis of networks based on Self-Comparative Diagnosis Model and g-good-neighbor property. *Journal of Computer and System Sciences* **2025**, p. 103698.
267. Xiang, D.; Hsieh, S.Y.; et al. G-good-neighbor diagnosability under the modified comparison model for multiprocessor systems. *Theoretical Computer Science* **2025**, *1028*, 115027.
268. Papoutsoglou, E.A.; Faria, D.; Arend, D.; Arnaud, E.; Athanasiadis, I.N.; Chaves, I.; Coppens, F.; Cornut, G.; Costa, B.V.; Ćwiek-Kupczyńska, H.; et al. Enabling reusability of plant phenomic datasets with MIAPPE 1.1. *New Phytologist* **2020**, *227*, 260–273.
269. Heil, B.J.; Hoffman, M.M.; Markowitz, F.; Lee, S.I.; Greene, C.S.; Hicks, S.C. Reproducibility standards for machine learning in the life sciences. *Nature methods* **2021**, *18*, 1132–1135.
270. Wang, M.; Wang, S. Diagnosability of Cayley graph networks generated by transposition trees under the comparison diagnosis model. *Annals of Applied Mathematics* **2016**, *32*, 166–173.
271. Wang, M.; Ren, Y.; Lin, Y.; Wang, S. The tightly super 3-extra connectivity and diagnosability of locally twisted cubes. *American Journal of Computational Mathematics* **2017**.
272. Wang, S.; Wang, M. The strong connectivity of bubble-sort star graphs. *The Computer Journal* **2019**, *62*, 715–729.
273. Boubin, J.; Burley, C.; Han, P.; Li, B.; Porter, B.; Stewart, C. Marble: Multi-agent reinforcement learning at the edge for digital agriculture. In Proceedings of the 2022 IEEE/ACM 7th symposium on edge computing (SEC). IEEE, 2022, pp. 68–81.
274. Zhu, F.; Huang, F.; Yu, Y.; Liu, G.; Huang, T. Task offloading with llm-enhanced multi-agent reinforcement learning in uav-assisted edge computing. *Sensors* **2024**, *25*, 175.
275. Liu, K.; Tang, Z.; Wang, D.; Wang, Z.; Li, X.; Zhao, B. Coherent: Collaboration of heterogeneous multi-robot system with large language models. In Proceedings of the 2025 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2025, pp. 10208–10214.
276. Wang, Q.; Ye, H.; Kim, J.; Ke, J.; Wang, Y.; Kuo, M.; Shao, Z.; Li, D.; Lin, Y.; Jiang, T.; et al. T2S-Bench & Structure-of-Thought: Benchmarking and Prompting Comprehensive Text-to-Structure Reasoning. *arXiv preprint arXiv:2603.03790* **2026**.
277. Brohan, A.; Chebotar, Y.; Finn, C.; Hausman, K.; Herzog, A.; Ho, D.; Ibarz, J.; Irpan, A.; Jang, E.; Julian, R.; et al. Do as i can, not as i say: Grounding language in robotic affordances. In Proceedings of the Conference on robot learning. PMLR, 2023, pp. 287–318.
278. Zitkovich, B.; Yu, T.; Xu, S.; Xu, P.; Xiao, T.; Xia, F.; Wu, J.; Wohlhart, P.; Welker, S.; Wahid, A.; et al. Rt-2: Vision-language-action models transfer web knowledge to robotic control. In Proceedings of the Conference on Robot Learning. PMLR, 2023, pp. 2165–2183.
279. Zhang, D.; Sun, J.; Hu, C.; Wu, X.; Yuan, Z.; Zhou, R.; Shen, F.; Zhou, Q. Pure vision language action (vla) models: A comprehensive survey. *arXiv preprint arXiv:2509.19012* **2025**.
280. Jian, Y.; Tian, D.; Chen, X.J.; Wei, Z.Y.; Liang, C.W.; Wang, M.J.S. PI-VLA: Adaptive Symmetry-Aware Decision-Making for Long-Horizon Vision–Language–Action Manipulation. *Symmetry* **2026**, *18*, 394.
281. Guan, W.; Hu, Q.; Li, A.; Cheng, J. Efficient vision-language-action models for embodied manipulation: A systematic survey. *arXiv preprint arXiv:2510.17111* **2025**.

282. Yu, Z.; Wang, B.; Zeng, P.; Zhang, H.; Zhang, J.; Gao, L.; Song, J.; Sebe, N.; Shen, H.T. A survey on efficient vision-language-action models. *arXiv preprint arXiv:2510.24795* **2025**.
283. Min, X.; Ye, Y.; Xiong, S.; Chen, X. Computer vision meets generative models in agriculture: Technological advances, challenges and opportunities. *Applied Sciences* **2025**, *15*, 7663.

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