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*Editorial*

# Advancing computer vision frontiers for sustainable precision agriculture

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Computer vision (CV) is rapidly transforming agricultural practices by enabling automated perception across various scales, from organ-level features in greenhouses to field-scale crop monitoring using unmanned aerial vehicles (UAVs). Recent studies have demonstrated effective object detection for weeds, fruits, and plant organs, along with high-throughput plant phenotyping and integrated perception-action loops in robotic systems (Sharma *et al*., 2024; Li *et al*., 2024; Zhang *et al*., 2025; Wang *et al*., 2025). Deep learning detectors, particularly modern YOLO variants, along with transformer-based architectures, are now routinely benchmarked on agricultural datasets and are increasingly optimized for edge deployment (Sharma *et al*., 2024; Li *et al*., 2024). Simultaneously, UAV and sensor-fusion pipelines are advancing to provide timely agronomic intelligence for growth monitoring, stress detection, and yield prediction (Wang *et al*., 2024; Impollonia *et al*., 2024; Wang *et al*., 2025). In postharvest food safety, UV-fluorescence imaging combined with deep learning techniques (such as YOLO, CNN, and ANN) has demonstrated promise for the rapid screening of aflatoxin in cocoa beans (Sadimantara *et al*., 2023; Sadimantara *et al*., 2024a; Sadimantara *et al*., 2024b). Complementing these advances, a recent study on *Citrus reticulata* (cv. Batu 55) demonstrated that combining reflectance and fluorescence images with a DCNN regression model (XSE-ResNet50) accurately predicts SSC, acidity, firmness, and the Brix–acid ratio (Al-Riza *et al*., 2024).

This editorial synthesizes and highlights advances in three key areas, first, robust detection in unstructured field conditions; second, speed–accuracy–compute trade-offs that facilitate real-time deployment; and third, the translation of visual perception into agronomic decision-making. It emphasizes evidence for model generalizability and actionable outputs while outlining policy and research priorities to accelerate the trustworthy adoption of precision agriculture (Bjerge *et al*., 2024; Hasan *et al*., 2025; Alex *et al*., 2025).

Field deployment of CV systems in agriculture is primarily constrained by generalization issues and data scarcity. Field conditions change due to factors such as phenology, illumination, occlusion, and background clutter, making it challenging for models trained in one environment to transfer reliably across different sites and seasons. For instance, in winter-wheat weed detection, authors specifically highlight gaps in dataset diversity and model adaptability as significant bottlenecks. This has led to the release of multi-species datasets and the systematic benchmarking of state-of-the-art detectors and transformer architectures (Li *et al*., 2024). Complementary research indicates that non-local modeling and attention mechanisms enhance global context and improve the recognition of small or partially occluded targets, all without incurring prohibitive computational overhead (Li *et al*., 2024; Wang *et al*., 2024).

A second constraint relates to the balance between speed, accuracy, and computational requirements for real-time operation. Comparative studies show that recent YOLO generations can exceed classical two-stage pipelines in accuracy while achieving significantly lower inference times. This enables practical deployment in the field. In several weed-detection benchmarks, these models demonstrated strong mAP with latency in the sub-tens-of-milliseconds range (Sharma *et al*., 2024; Zoubek *et al*., 2025; Kalezhi and Shumba, 2025). Hardware-aware optimization and quantization techniques, such as TensorRT, help maintain high frame rates on embedded platforms with only modest accuracy trade-offs. This is essential for on-robot or UAV autonomy, where energy and compute budgets are limited (Li *et al*., 2024).

Ultimately, impact depends on converting perception into action. Emerging end-to-end systems now integrate visual inference with robotic manipulation and control. For instance, beehive handling systems combine YOLO/DeepSORT tracking with hybrid control to enhance accuracy, stability, and cycle time (Wang *et al*., 2025). In mechanized harvesting, attention-enhanced detectors and geometric reasoning have enabled reliable localization of pick points for small, occluded targets. This advancement moves vision pipelines beyond passive detection and toward executable agronomic operations (Wang *et al*., 2024; Deng *et al*., 2024; Zhang *et al*., 2025).

Scientists and engineers are continuously refining model architectures to address the visual challenges presented by agricultural scenes, dense canopies, small targets, and heterogeneous multi-class settings, all while balancing accuracy with deployment feasibility (Sharma *et al*., 2024; Wang *et al*., 2024; Li *et al*., 2024). In the context of weed control, combining morphology-aware meta-learning with object detection has enhanced transferability across datasets and locations. This marks significant progress toward site-independent detection and more sustainable reductions in herbicide use (Hasan *et al*., 2025; Zoubek *et al*., 2025).

Translational value relies on delivering outputs that align with agronomic calendars and decision thresholds. Agronomists and advisors seek actionable predictions, such as early-season yield estimates during tillering or ripening to inform nitrogen management, as well as lodging maps that facilitate harvest logistics (Impollonia *et al*., 2024; Zhang *et al*., 2024). On the operational side, growers and service providers benefit from edge-deployable detectors and optimized pipelines—such as quantization and acceleration—that ensure field-speed inference (Sharma *et al*., 2024; Li *et al*., 2024). In protected cultivation, low-cost phenotyping with pan–tilt–zoom cameras allows for high-accuracy capture of organ-level traits and generates data streams that support both daily operations and artificial intelligence (AI) model development (Pham *et al*., 2024). Ecologists and biodiversity managers are utilizing time-lapse detection and classification to monitor arthropod abundance in relation to floral resources, beyond just production. Motion-informed filtering helps reduce false positives, allowing for scalable, long-term observation (Bjerge *et al*., 2024). Actors focused on food quality and safety are also advancing non-destructive analytics, such as fluorescence hyperspectral imaging for estimating sucrose in apples and hyperspectral screening for detecting pesticide residues in olives (Zhan *et al*., 2024; Martínez Gila *et al*., 2024).

Realizing these gains at scale will require supportive data and governance infrastructures. Policymakers and funders should prioritize open, findable, accessible, interoperable, and reusable (FAIR) datasets, as well as cross-site benchmarks, to mitigate vendor lock-in, accelerate reproducibility, and strengthen robustness—priorities consistently underscored in recent surveys and thematic reviews of UAV-enabled monitoring and land-use dynamics (Wang *et al*., 2024a; Ma *et al*., 2024; Mathewos *et al*., 2024; Qin *et al*., 2024; Wang *et al*., 2025).

Building trustworthy agricultural AI starts with benchmarking and utilizing open, transferable data. Curated and diverse datasets enriched with agronomic metadata—covering phenology, management practices, and environmental context—provide a solid foundation for reproducible evaluations and fair comparisons across methods. Recent releases, such as multi-species winter-wheat weed image collections, have facilitated systematic ablation of architectural components, including spatial attention, non-local blocks, and deformable convolutions, clarifying the sources of performance gains (Li *et al*., 2024). In parallel, strategies such as semi-supervised annotation, morphology-based grouping, and lightweight two-stage pipelines are effectively reducing labelling burdens while preserving generalization. These approaches are successfully scaling training corpora without sacrificing quality (Khanna *et al*., 2024; Calderara-Cea *et al*., 2024; Hasan *et al*., 2025).

Equally important is the delivery of edge-ready, explainable models that meet real-time constraints in the field. Comparative studies indicate that newer YOLO iterations provide state-of-the-art accuracy for weed detection, with YOLOv11 offering particularly fast inference suitable for embedded hardware (Sharma *et al*., 2024). Hardware-aware optimizations, such as TensorRT FP16 quantization, help maintain high throughput with minimal accuracy loss. This is essential for deploying mobile robots and UAVs that operate under tight energy and compute constraints (Li *et al*., 2024). Where systems are operated by non-technical users, implementing explainable interfaces for detections and tracking enhances transparency and auditability, thereby supporting safer and more confident decision-making (Alex *et al*., 2025).

Progress also depends on integrating and fusing sensing modalities into agronomic workflows. By combining ground-based imaging, PTZ-camera phenotyping, and UAV remote sensing, we can connect organ-, canopy-, and field-scale insights to actionable prescriptions (Pham *et al*., 2024; Wang *et al*., 2024; Wang *et al*., 2025). Demonstrated pipelines effectively translate maps into management strategies, including early-season yield predictions to guide nitrogen decisions, lodging segmentation to streamline harvesting logistics, and site-specific treatment targeting that reduces inputs while maintaining efficacy (Impollonia *et al*., 2024; Zhang *et al*., 2024). As autonomy expands for workers and animals, rigorous validation of trajectory error, vibration, and operational stability remains essential. Recent studies on beehive handling provide concrete metrics and controls (Wang *et al*., 2025). Sustained training for agronomists and technicians in uncertainty literacy and basic model auditing will be essential for the safe and effective large-scale adoption of these practices (Bjerge *et al*., 2024; Alex *et al*., 2025).

Recent progress indicates a significant advancement in managing fine-grained agricultural targets. Attention-enhanced and transformer-augmented detectors, combined with geometric post-processing, are enhancing the recognition and localization of pick points for small, occluded structures that are crucial to harvesting workflows (Wang *et al*., 2024; Zhang *et al*., 2025). Parallel gains in dense-object detection are being achieved through high-resolution inputs and purpose-built datasets, as exemplified by blueberry canopy imaging for joint detection, counting, and maturity estimation (Deng *et al*., 2024). Postharvest quality analytics are also advancing. Fluorescence hyperspectral imaging, combined with wavelength selection and ensemble learning, shows promising accuracy in predicting sucrose concentration in apples, while pixel-wise hyperspectral classification demonstrates feasibility for detecting pesticide residues and estimating the time since application in freshly harvested olives (Martínez Gila *et al*., 2024; Zhan *et al*., 2024).

Opportunities also arise from increased robustness and ecological diversity. In weed management, morphology-aware classification using Siamese networks integrated into modern detectors provides site-independent performance across multiple public datasets, which is essential for scalable, geography-agnostic deployment (Hasan *et al*., 2025). Lightweight, quantized YOLO variants enable real-time inference in field conditions, effectively balancing speed and accuracy on embedded hardware (Sharma *et al*., 2024). Beyond production plots, biodiversity and pollination monitoring now utilize time-lapse detection pipelines and EfficientNet-based classification. Motion-informed filtering reduces false positives, and explainable interfaces translate bee detection events into stakeholder-friendly reports (Bjerge *et al*., 2024; Alex *et al*., 2025). High-throughput phenotyping at scale benefits from pan-tilt-zoom camera systems, which capture zoomed organ-level traits with high precision. This generates continuous data streams for operational decision-making and future model training (Pham *et al*., 2024). Finally, low-altitude UAV remote sensing is increasingly integrating with machine and deep learning for growth, stress, and yield analytics, strengthening the connection from multiscale imagery to actionable agronomic intelligence (Wang *et al*., 2024; Wang *et al*., 2025).

Evidence from the cited literature indicates that CV and deep learning are evolving from detection-only prototypes to integrated perception-decision-action systems. Enhancements in dataset quality, architectural design—particularly attention mechanisms and non-local modeling—and hardware-aware optimization now support robust performance in complex field scenes and enable real-time deployment on edge platforms (Sharma *et al*., 2024; Li *et al*., 2024). Several exemplars effectively close the loop from sensing to management: robotic manipulation and safe material handling, early yield prediction to inform nitrogen management, lodging maps that streamline harvesting logistics, and nondestructive quality screening to guide postharvest decisions (Impollonia *et al*., 2024; Zhang *et al*., 2024; Zhan *et al*., 2024; Wang *et al*., 2025).

Scaling impact responsibly will require the expansion of open, diverse datasets enriched with agronomic context. It will also necessitate prioritizing edge-deployable, explainable models that are explicitly evaluated on the speed–accuracy–compute frontier. Additionally, there should be a tighter integration of sensing modalities to ensure that outputs directly translate into actionable agronomic interventions. Sustained investment in safety, skills, and farmer-centered validation should accompany these technical advances. With coordinated efforts among researchers, practitioners, and policymakers, vision-enabled agriculture can achieve higher productivity, reduced inputs, and greater ecological resilience (Bjerge *et al*., 2024; Wang *et al*., 2025; Alex *et al*., 2025).

**Ethical approval and informed consent**

Not applicable.

**Data availability**
Not applicable.

**Conflict of interest**
None to declare.

**Author's contribution**
Conceptualization, writing – original draft, review and editing: Yusuf Hendrawan. The author approved the final version.

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