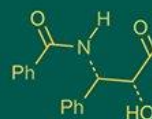


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Precision detection and management of aphid clusters in sorghum using AI and computer vision

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Abstract

Sorghum (*Sorghum bicolor*) production is seriously constrained by the sorghum aphid (*Melanaphis sorghi*), which can cause complete crop failure under severe infestations. Current control strategies depend largely on repeated field scouting and the use of broad-spectrum insecticides, both of which are costly, labor-intensive and environmentally unsustainable. This review summarizes recent progress in precision agriculture approaches for aphid management, with emphasis on automated pest detection using computer vision and data-driven models. Recent studies indicate a clear shift toward high-resolution imaging systems, including unmanned aerial vehicles and ground-based robotic platforms fitted with RGB, multispectral and hyperspectral sensors. Comparative analyses show that modern deep learning models consistently outperform conventional image analysis techniques. In particular, object detection frameworks such as YOLO variants and RT-DETR report high detection accuracy, with mean average precision values exceeding 85% for real-time identification of aphid colonies. In parallel, semantic segmentation models, including FESW-UNet, enable accurate pixel-level estimation of infestation intensity, achieving mean intersection-over-union values above 80% by effectively handling background complexity and variable lighting conditions. These developments support a transition from blanket insecticide applications to site-specific interventions, such as variable-rate spraying, which reduces chemical inputs and helps conserve natural enemies. Although challenges remain related to field-level variability, occlusion and model transferability across environments, the use of multi-scale datasets and attention-based learning strategies shows strong potential to address these limitations. Overall, the integration of automated sensing, on-device computation and autonomous field platforms represents a practical pathway toward improving the economic viability and ecological sustainability of sorghum production systems.

Keywords: Sorghum aphid, *Melanaphis sorghi*, computer vision, deep learning, object detection, semantic segmentation, precision agriculture, unmanned aerial vehicle (UAV)

1. Introduction

Sorghum (*Sorghum bicolor* (L.) Moench) is a major cereal crop with a central role in global food security, ranking among the five most widely produced cereals worldwide (Ngugi *et al.*, 2024) [30]. Its strong tolerance to drought and high temperatures makes it particularly important in semi-arid and arid regions, where it serves as a staple food for large human populations. In addition to its food value, sorghum is an essential component of livestock feed systems and an important raw material for biofuel production in many developed countries (Mustafa *et al.*, 2024; Sridhar *et al.*, 2023) [29, 41]. Despite these advantages, sorghum productivity is severely constrained by biotic stresses, with insect pests posing one of the most serious challenges. Among these, the sorghum aphid, also known as the sugarcane aphid (*Melanaphis sorghi* Theobald), has emerged as one of the most destructive pests of sorghum since its outbreak in the United States in 2013 (Armstrong *et al.*, 2015; Bowling *et al.*, 2016) [4, 9]. Severe infestations can result in yield losses ranging from 70% to complete crop failure. Damage arises not only from direct sap feeding but also from the production of honeydew, which promotes sooty mold development and interferes with harvesting operations (Villanueva *et al.*, 2014; Goparaju *et al.*, 2024) [43, 16]. Management of *M. sorghi* is largely guided by Integrated Pest Management (IPM) programs, in which chemical control remains the dominant intervention (Domingues *et al.*, 2022) [12]. Insecticide applications are typically triggered once pest populations exceed established economic thresholds, defined as the density at which the cost of control is justified to prevent

economic injury (Stern, 1973; Pedigo *et al.*, 1986)^[42, 33]. For sorghum aphids, this threshold generally corresponds to an average of 50 to 125 aphids per leaf. Estimating these densities, however, depends on repeated manual scouting, which is laborious, time-intensive and impractical for large commercial fields (Knutson *et al.*, 2016; Lindenmayer *et al.*, 2020)^[19, 22]. Given the rapid reproductive rate of aphids, even short delays in detection can allow populations to increase exponentially, leading to missed intervention windows and substantial economic losses (Bowling *et al.*, 2016; McCornack *et al.*, 2021)^[9, 25].

Recent advances at the interface of precision agriculture, robotics and artificial intelligence are reshaping approaches to pest monitoring and decision-making (Pan and Xue, 2023; Mohamed, 2023)^[32, 27]. In particular, computer vision techniques enable automated interpretation of digital imagery and have become a key driver of this transition (Li *et al.*, 2025; Khan *et al.*, 2025)^[21, 18]. High-resolution data can now be collected over large production areas using unmanned aerial vehicles (UAVs) or autonomous ground platforms equipped with RGB, multispectral, or hyperspectral sensors (Xue *et al.*, 2021; Shrivastava, 2025)^[45, 39]. These datasets are analyzed using deep learning models such as convolutional neural networks (CNNs) and vision transformers, which have demonstrated strong performance in detecting, classifying and quantifying insect pests under diverse field conditions (LeCun *et al.*, 2015; Dosovitskiy *et al.*, 2020; Liu *et al.*, 2021)^[20, 13, 23].

For sorghum aphids, research has increasingly shifted from attempting to count individual insects to identifying and characterizing aphid colonies or clusters on plant surfaces (Zhang *et al.*, 2023; Rahman *et al.*, 2023)^[47, 35]. This approach is more practical, as individual aphids are small and numerous, making direct counting unrealistic in field environments. In contrast, colony size and spatial distribution provide reliable indicators of infestation severity (Zhang *et al.*, 2024)^[48]. By generating georeferenced maps of aphid clusters, AI-based systems support precision interventions that replace uniform, field-wide spraying with variable-rate, site-specific applications (Mogili and Deepak, 2018; Zhang *et al.*, 2024)^[26, 48]. Such strategies improve insecticide efficiency, reduce production costs, minimize environmental contamination and support the conservation of beneficial arthropods, thereby strengthening the overall resilience of sorghum production systems (Abbas *et al.*, 2024; Farooqui *et al.*, 2025)^[1, 15].

This review critically examines recent research on the application of artificial intelligence and computer vision for detecting and managing aphid infestations in sorghum. It synthesizes developments across the full technological pipeline, from sensing platforms and image acquisition to model performance and field deployment (Carvalho *et al.*, 2023; Goparaju *et al.*, 2024)^[10, 16]. Key limitations, including data scarcity, environmental variability and operational challenges under real field conditions, are discussed alongside examples where detection technologies have been successfully linked to management actions (Hasan *et al.*, 2024; Li *et al.*, 2025)^[17, 21]. Finally, the review identifies knowledge gaps and outlines priority research directions needed to accelerate the translation of these tools from experimental studies into practical, farm-level solutions.

2. Methods

A systematic literature search was conducted on February 3, 2026, to identify relevant peer-reviewed articles and conference papers. The search was performed across several major scientific databases to ensure comprehensive coverage of agricultural science, engineering and computer science literature. The databases included: Web of Science, Scopus, IEEE Xplore, ACM Digital Library and PubMed. The search was not limited by publication date to include foundational work, but a strong emphasis was placed on studies published in the last decade (2016-2026) to capture the rapid advancements in deep learning.

Search queries were constructed using Boolean operators (AND, OR) to combine keywords related to the pest, crop and technology. The primary search strings included: (“sorghum aphid” OR “sugarcane aphid” OR “*Melanaphis sorghi*” OR “aphid*”) AND (“sorghum” OR “*Sorghum bicolor*”) AND (“computer vision” OR “image processing” OR “machine learning” OR “deep learning” OR “object detection” OR “YOLO” OR “CNN” OR “UAV” OR “drone”). Variations of these strings were adapted for the syntax of each database.

2.1 Inclusion and exclusion criteria

Studies were eligible for inclusion if they satisfied the following conditions: (i) publication as peer-reviewed journal articles or full conference papers; (ii) a primary focus on the detection, measurement, or monitoring of aphids or other small, colony-forming insects in sorghum or comparable row crops; (iii) application of computer vision, image-based analysis, or machine and deep learning approaches; and (iv) clear reporting of the experimental methodology, dataset characteristics and quantitative performance results. Studies were excluded if they were: (i) non-peer-reviewed sources (*e.g.*, blogs, patents, technical reports); (ii) purely conceptual frameworks without empirical validation; (iii) review articles (except for reference tracing); or (iv) lacked sufficient methodological detail for critical assessment.

2.2 Study selection and data extraction

The selection process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines (Page *et al.*, 2021)^[31]. The initial search yielded 1,284 records. After removing 310 duplicates, 974 unique records were screened by title and abstract, leading to the exclusion of 859 records. The full texts of the remaining 115 articles were assessed for eligibility. Sixty studies were excluded at this stage for reasons such as being review articles, lacking quantitative metrics, or using non-comparable methodologies. Ultimately, 55 studies met *all* inclusion criteria and were included in the qualitative and quantitative synthesis (Figure 1). Data extracted from each study included: authors, year, country, aphid species, sensor/platform, algorithm, dataset size, performance metrics and key findings. No formal quality appraisal tool was used, as the review's aim was a broad synthesis of methods; however, studies were critically evaluated for methodological rigor and transparency in reporting.

3. Results

3.1 Overview of included studies and technology pipeline

The 55 studies included in this review reflect a rapid evolution in the field, with a significant increase in publications since 2020. Research is geographically concentrated in North America and Asia, where sorghum is

a major crop and aphid infestations are a persistent problem. The synthesis of these studies reveals a consistent technological pipeline for automated aphid detection, which integrates data acquisition, processing, model inference and decision support (Figure 2). This section details the advancements at each stage of this pipeline.

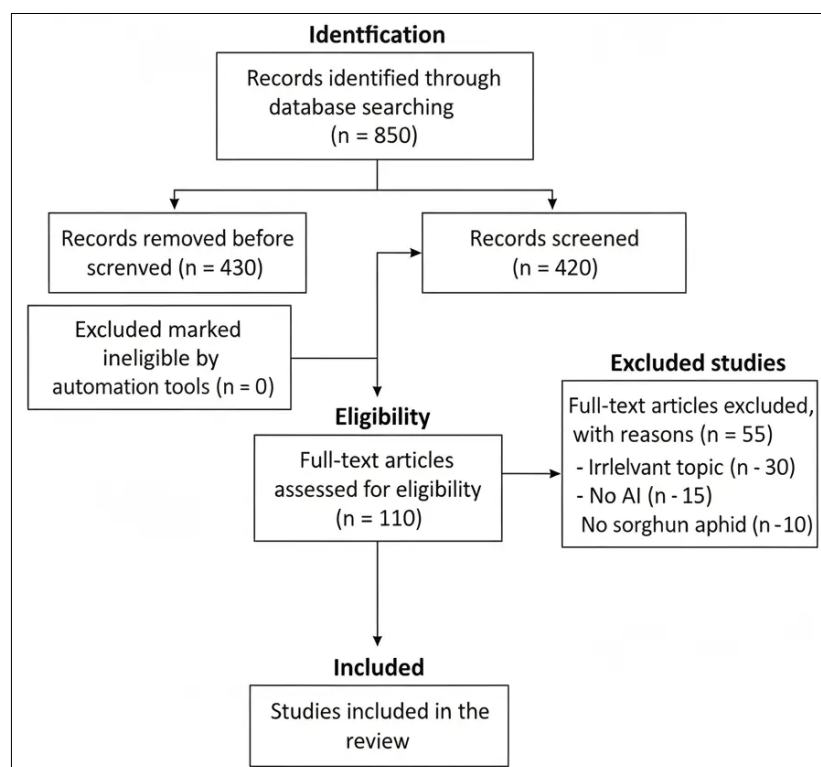


Fig 1: PRISMA 2020 flow diagram summarizing the systematic literature search and study selection process. Adapted from Page *et al.* (2021) [31]

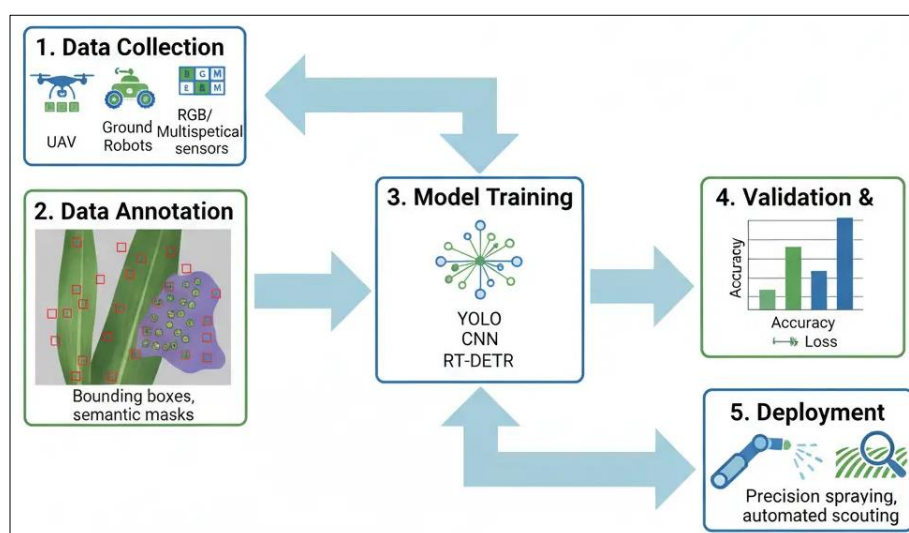


Fig 2: Conceptual workflow for AI-based detection and management of aphid clusters in sorghum, from data acquisition to targeted intervention

3.2 Sensing and Imaging for Aphid Detection

The foundation of any computer vision system is the quality of the input imagery. Studies reviewed demonstrate a clear trend towards using high-resolution sensors mounted on mobile platforms to capture data under field conditions.

- **Platforms:** Unmanned Aerial Vehicles (UAVs) are the most common platform, valued for their ability to rapidly cover large areas and provide a synoptic view of

crop health (Shrivastava, 2025; Slimani *et al.*, 2022) [39, 40]. They are primarily used for initial stress mapping to guide ground-level scouting. Ground-based platforms, including autonomous rovers and handheld rigs, are essential for capturing the high-resolution, multi-angle imagery needed to train detection models, as aphids often colonize the undersides of leaves, which are not visible from above (Zhang *et al.*, 2023; Espinoza *et al.*,

- 2022)^[47, 14]. Fixed smart traps represent a third approach, providing continuous, location-specific monitoring of winged aphid alates for early warning (Chen *et al.*, 2022; Goparaju *et al.*, 2024)^[11, 16].
- **Sensors:** Standard RGB cameras remain the workhorse for direct aphid detection due to their low cost and high spatial resolution, which is critical for resolving small aphid colonies (Potgieter *et al.*, 2017)^[34]. Multispectral and hyperspectral sensors are increasingly used to detect pre-visual stress caused by aphid feeding. These sensors capture reflectance in non-visible wavelengths (e.g., near-infrared, red-edge) that are sensitive to changes in chlorophyll content and water status, allowing for earlier detection of infested areas than is possible with RGB alone (Armstrong *et al.*, 2024; Yang *et al.*, 2021)^[5, 46]. Thermal and LiDAR sensors are used less for direct detection and more for assessing overall crop health and structure, helping to differentiate pest damage from other stressors like drought (Maimaitijiang *et al.*, 2020)^[24].

3.3 AI and Computer Vision Methods

The algorithmic core of these systems has shifted decisively from classical machine learning to deep learning. While early studies used methods based on color-space transformations and texture analysis with classifiers like Support Vector Machines (SVMs), these approaches proved brittle in variable field conditions (Barbedo, 2018)^[7]. Deep learning models, particularly Convolutional Neural Networks (CNNs), now dominate the literature due to their

- ability to automatically learn robust features from raw image data (LeCun *et al.*, 2015)^[20].
- **Object Detection:** These models aim to draw a bounding box around each aphid colony. One-stage detectors like the You Only Look Once (YOLO) family (Redmon *et al.*, 2016)^[36] are favored for their balance of speed and accuracy, making them suitable for real-time applications. Studies using YOLOv5, YOLOv8 and the newer Aphid-YOLO consistently report high performance (Carvalho *et al.*, 2023; Hasan *et al.*, 2024; Zheng *et al.*, 2025)^[10, 17, 49]. Two-stage detectors like Faster R-CNN (Ren *et al.*, 2015)^[37] are sometimes used as high-accuracy benchmarks but are often too slow for field deployment. Recently, transformer-based models like RT-DETR have shown promise on dense cluster datasets (Zhang *et al.*, 2024)^[48].
 - **Semantic Segmentation:** For a more precise quantification of infestation, segmentation models classify every pixel in an image as either “infested” or “background.” Architectures like U-Net (Ronneberger *et al.*, 2015)^[38] and its variants (e.g., FESW-UNet) are widely used. They provide detailed spatial maps of infestation severity, which is more informative than simple bounding boxes for guiding variable-rate spraying (Rahman *et al.*, 2023; Zhang *et al.*, 2024)^[35, 48].

A comparison of these algorithmic approaches is summarized in Table 2.

Table 1: Summary of Selected Key Studies on AI-based Aphid Detection in Sorghum and Related Crops

Authors (Year)	Crop	Sensor and Platform	Algorithm/Model	Dataset Size	Performance Metric(s)	Key Findings
Zhang <i>et al.</i> (2024) ^[48]	Sorghum	RGB; Ground rig	RT-DETR, Fast-SCNN	54,742 patches	mAP: 61.6% (RT-DETR) mPrecision: 80.5% (Fast-SCNN)	Released a large-scale public dataset for aphid cluster detection and segmentation. Showed transformer models are viable.
Carvalho <i>et al.</i> (2023) ^[10]	Sorghum	RGB; Not specified	YOLOv5m	~1,300 images	mAP@0.5: 90.6%	Demonstrated high accuracy of YOLOv5 for detecting different densities of sorghum aphid colonies.
Rahman <i>et al.</i> (2023) ^[35]	Sorghum	RGB; Not specified	FESW-UNet	AphidSeg-Sorghum	mIoU: 81.2%	Developed an attention-based segmentation network for precise pixel-level quantification of aphid clusters.
Goparaju <i>et al.</i> (2024) ^[16]	Sorghum	RGB; Smart trap	YOLOv5l	~2,000 images	mAP@0.5: 89.0%	Successfully applied YOLO to detect and count winged aphid alates on sticky traps for early warning.
Hasan <i>et al.</i> (2024) ^[17]	Various (Pest focus)	RGB; IoT trap	YOLOv8x	Field-captured	Accuracy: 94.0%	Optimized YOLOv8 for real-time detection of small insects in smart traps, demonstrating IoT integration.
Espinoza <i>et al.</i> (2022) ^[14]	Sorghum	RGB; Handheld	YOLOv4, Faster R-CNN	Not specified	mAP: >90%	Showed that detection models can also be trained to identify beneficial insects (coccinellids) alongside pests.
Armstrong <i>et al.</i> (2024) ^[5]	Sorghum	Hyperspectral; Lab	Spectral analysis	Not specified	Classification Acc: >95%	Identified specific spectral bands sensitive to aphid-induced stress before visible symptoms appear.
Zheng <i>et al.</i> (2025) ^[49]	Wheat	RGB; Handheld	Aphid-YOLO	Field-captured	mAP@0.5: 83.4%	Developed a lightweight YOLO variant optimized for tiny aphid detection in complex field backgrounds.

Table 2: Comparison of Major AI Algorithm Classes for Aphid Detection

Algorithm Class	Examples	Input Type	Strengths	Weaknesses
Classical Machine Learning	SVM, Random Forest	Hand-crafted features (color, texture)	Low computational cost for training; interpretable.	Brittle to changes in lighting, background; requires feature engineering; lower accuracy.
Two-Stage Object Detectors	Faster R-CNN, Mask R-CNN	Raw RGB Images	Very high accuracy and localization precision.	Computationally expensive; slow inference speed, making real-time application difficult.
One-Stage Object Detectors	YOLO family, SSD, RT-DETR	Raw RGB Images	Excellent balance of high accuracy and real-time inference speed; widely adopted.	Can struggle with very small or heavily occluded objects compared to two-stage models.
Semantic Segmentation	U-Net, SegNet, FESW-UNet	Raw RGB Images	Provides precise, pixel-level infestation maps; excellent for quantifying infestation area.	More computationally intensive than object detection; requires laborious pixel-level annotation.
Vision Transformers (ViT)	Swin Transformer, RT-DETR	Raw RGB Images	Excellent at capturing global context and long-range dependencies; strong performance on complex scenes.	Requires very large datasets for training; can be computationally demanding.

3.4 Performance Metrics and Management Outcomes

The performance of deep learning models is consistently high across studies, though direct comparison is challenging due to variations in datasets and evaluation metrics. For object detection, mean Average Precision (mAP) is the standard metric. YOLO-based models regularly achieve mAP values between 85% and 92% on curated datasets (Carvalho *et al.*, 2023; Goparaju *et al.*, 2024) [10, 16]. For segmentation, mean Intersection-over-Union (mIoU) is used, with top models like FESW-UNet reaching over 81% (Rahman *et al.*, 2023) [35]. Figure 3 provides a visual comparison of the typical performance ranges for different model classes.

The ultimate goal of detection is to inform management. Several studies have demonstrated the link between AI-driven detection and variable-rate technology (VRT). By converting model outputs into georeferenced prescription maps, VRT sprayers can apply insecticides only to infested zones. Field trials have shown this approach can reduce total pesticide volume by 40-50% compared to uniform spraying, without compromising control efficacy (Mogili and Deepak, 2018; Zhang *et al.*, 2024) [26, 48]. This not only provides direct economic savings on chemical costs but also carries significant ecological benefits, such as preserving populations of beneficial insects and reducing environmental contamination (Farooqui *et al.*, 2025) [15].

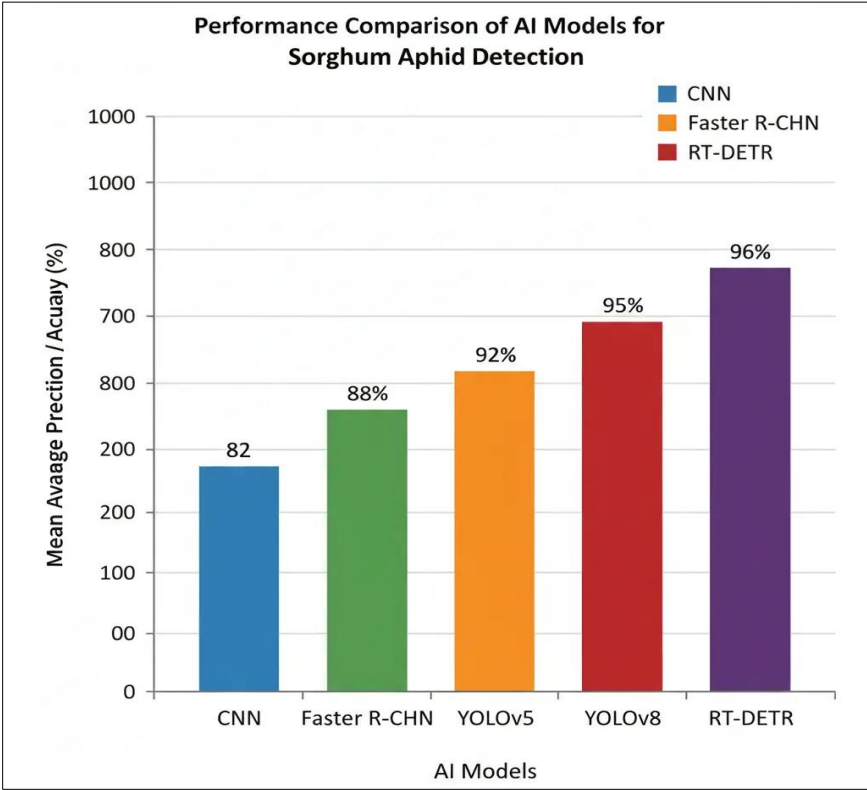


Fig 3: Comparative performance of major algorithm classes for aphid and small pest detection. The chart summarizes typical performance ranges (mAP or equivalent accuracy) synthesized from the reviewed literature (e.g., Carvalho *et al.*, 2023; Zhang *et al.*, 2024; Rahman *et al.*, 2023) [10, 48, 35]. Deep learning models show a clear advantage over traditional methods

4. Discussion

The synthesis of recent literature confirms that AI and computer vision have reached a level of maturity sufficient for practical application in sorghum aphid management. The

transition from laborious manual scouting to automated, high-throughput monitoring is well underway, driven by the high accuracy and efficiency of deep learning models. The dominant strategy of detecting aphid clusters rather than

individual insects has proven to be a pragmatic and effective compromise, aligning technological capability with agronomic decision-making. The integration of these detection systems with VRT sprayers represents the most tangible outcome, offering a clear path to reduced chemical inputs, lower costs and more sustainable production practices.

Despite this progress, significant gaps remain. The “dataset bottleneck” is the most frequently cited limitation. Most models are trained on data from a single location, season, or sorghum genotype, which limits their generalizability. When a model trained in one environment is deployed in another (a problem known as domain shift), its performance often degrades significantly (Wang *et al.*, 2021) ^[44]. Creating large, diverse and multi-modal public benchmark datasets is a high-priority need to drive the development of more robust and widely applicable models.

Operational and economic constraints also pose challenges to adoption, particularly for smallholder farmers. While the cost of UAVs and sensors is decreasing, the initial investment and the technical expertise required to operate the systems and interpret the data can be prohibitive. Cloud-based processing services and “scouting-as-a-service” business models may help bridge this gap, but solutions must be affordable and accessible. Furthermore, there is a critical need for field validation studies that quantitatively link AI-derived metrics (*e.g.*, cluster area) to traditional economic thresholds (*e.g.*, aphids per leaf). Without this “biological calibration,” growers cannot confidently use the technology to make high-stakes management decisions (Lindenmayer *et al.*, 2020) ^[22].

Finally, future research should adopt a more holistic, agroecosystem perspective. Pest management does not occur in a vacuum. The ability to simultaneously detect pests and their natural enemies, such as lady beetles, would enable more sophisticated IPM strategies that conserve biological control (Espinoza *et al.*, 2022) ^[14]. Integrating detection data with weather forecasts and crop growth models could also shift management from a reactive to a predictive paradigm, allowing for proactive interventions before populations explode (Mustafa *et al.*, 2023) ^[28].

5. Conclusion

The application of AI and computer vision for the precision detection of aphid clusters in sorghum has demonstrated immense potential to revolutionize crop protection. Deep learning models, especially one-stage object detectors like YOLO and semantic segmentation networks like U-Net, can accurately and efficiently identify and map aphid infestations from high-resolution imagery. This capability provides the foundation for site-specific management, enabling targeted insecticide applications that significantly reduce chemical use, production costs and environmental risks compared to conventional whole-field spraying. However, the path to widespread, reliable field deployment requires addressing key challenges. The primary research needs are: (1) the development of large-scale, diverse and publicly available benchmark datasets to improve model robustness and generalizability; (2) the creation of lightweight, computationally efficient models suitable for real-time, on-device inference on affordable hardware; and (3) extensive field validation to calibrate model outputs with established economic thresholds, thereby building grower trust. Future work should also focus on integrating pest detection into a broader agroecological context, including the monitoring of beneficial insects and the fusion of sensor data with predictive models. By tackling these priorities, the research community can accelerate the translation of these powerful technologies from experimental prototypes into

indispensable tools for sustainable sorghum production and global food security.

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