



A Comprehensive Review: Statistical Analytical Review of Multimodal Weed Detection and Management Strategies Using Graph Network

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Abstract: As a reply to the tremendous complexity and extent of modern agricultural weed control, a statistical analytical review is being presented in this study of all modern scholarly contributions in the area of deep learning (DL), optimization algorithms, ecological control systems, and biochemical valorisation approaches. Its main objective is to bundle these disparate methods into a single benchmarking framework on six performance criteria: Weed Detection Accuracy, Precision, Reliability, Time Complexity, Memory Complexity, and Makespan Sets. Therefore, methodologies such as DC-YOLO, Efficient Net-based transfer learning, RSA-enhanced YOLOv3, SCR-DETR, and RCNN are compared in this review with approaches already using microbial weed suppression models, anaerobic bioreactors, and graph-based simulation techniques. Each of the above approaches is being evaluated both qualitatively and quantitatively while data were then gleaned from reported empirical findings or approximated through interpolation of cross-study performance. In the comparative matrix established through the dataset, detection efficiency, scalability, resource requirements, and robustness are displayed across a wide range of use cases; from UAV surveillance, thermal classifications, to mechanical weeding. All vision-based DL approaches score detection accuracies well above 93%, but the cost is increased memory usage and time complexity incurred when the complexity of the scene increases in process. Thus, this review identifies research gaps in data fusion, model interpretability, and real-world deployment, while proposing future integration pathways such as eco-AI coupling and secure visual processing for different scenarios. This work lays the groundwork for precision agriculture as an analytical resource in weed control events at some point from future technological applications in robust adaptive and environmentally sustainable weed control treatments in process.

Keywords: Weed Detection, Deep Learning, Precision Agriculture, Performance Benchmarking, Image Segmentation, Scenarios.

I. INTRODUCTION

Threatening food security by decreasing yields of food production, increasing farm management costs, and accelerating the development of herbicide resistance, weeds continue to menace the food crops of humankind in many parts of the world. As far as agricultural landscapes become more complex or intensified by climate variability, the traditional methods of weed control, such as manual removal, sprayer herbicide broadcast, and mechanical tillage, have failed in terms of scalability, precision, and sustainability. Intelligent, automatic weed detection and control systems are thus emerging, supported by the recent developments in computer vision, deep learning (DL), robotics, and ecological modelling sets. Thus, the importance of this study comes from the fragmented and silo-ed research currently existing in weed detection. Different methods have emerged-from convolutional neural networks, UAV imagery analytics and bio-reactor optimization to material-based sensing-but they all tend to operate within silos. Most of the literature reviews carried out so far are unfortunately quite narrow, concentrating on either image processing models or biochemical suppression strategies, without establishing synthesis cross-domain connection between algorithmic performances and real-life constraints in farming sets.

This work's motivation is to provide an integrated analytical perspective that assesses not only detection accuracy by different systems but also wider operational implications like those concerning system efficiency, trade-offs between time and memory, ecological complementarity, and real-time usability. Systematic comparison of techniques based on standardized metrics is urgent, especially as researchers and agritech developers develop scalable solutions either on edge devices or in dynamic field conditions. The contribution of the said study is a thorough statistical analytical review of 50 peer-reviewed methods extending from vision-based DL models (e.g. YOLOv5 variations, RCNN, SCR-DETR) to ecological interventions (e.g., microbial competition, stress induction), optimization frameworks (Neuro-IWO, hybrid Bell algorithm), and bio integrated processing systems (anaerobic baffled reactors). Each paper was studied extensively



into six primary categories into which the performance metrics had been extracted and normalized from quantitative data: Weed Detection Accuracy, Precision, Reliability, Time Complexity, Memory Complexity, and Makespan. These represent both technical performance as well as their applicability at field level; thus they address both "how well" and "how usable" dimensions of each method in process.

Beyond the technical synthesis, this research hence identifies under-explored convergence points such as graph-enhanced attention networks for spatio-temporal modelling, integration of cryptographic vision protection, and hybrid eco-AI models for closed-loop weed management. The review also pinpoints bottlenecks around generalization, data annotation scarcity, and environmental robustness, which need to be removed before these technologies can be adopted widely. Therefore, this paper can be considered a leaping foundational road map for interdisciplinary innovation in weed detection by aggregating and analysing empirical results over domains. It also supports the informed decision-making of researchers, policymakers, and Agri-tech developers on advanced weed control systems aligned with sustainable and precision agriculture goals.

II. IN DEPTH REVIEW OF EXISTING METHODS

The principal issue faced by precision agriculture is weed management in terms of its effects on crop productivity and competition for resources by invasive species. The most recent breakthroughs concerning computational weed identification pivot between deep learning and computer vision techniques, emphasizing the growing interest in Graph Neural Networks (GNNs), primarily due to their ability to model spatial dependencies and relational structures among objects. This really tightly iterative empirical-based review presents the GNN-based methodologies integrated into traditional machine learning and image-processing frameworks applied in agricultural weed identification sets with the context of weed ecology. Conventional machine learning and deep learning methods such as AlexNet–SVM pipelines [1], MobileNet classifiers with graph-cut segmentation [7], and transfer learning-enhanced Efficient Net models [43] have been proven effective in distinguishing weed species within diverse agro-ecological settings, yet they do not include inter-object contextual information critical to differentiating morphologically close plant species. Hence, this limitation has led to a search for solutions in terms of graph-based methods, which set weed detection as a structured data problem involving relationships between neighbouring pixels, objects, or spatial regions.

Table 1. Model's Empirical Review Analysis

Ref. No.	Method Used	Key Findings	Strengths	Limitations	Recommendation
1	Superpixel + AlexNet–SVM	Detected weeds using segmented regions	Strong spatial + classification	Static datasets only	Use graph-based relational models
2	Graph Theory on Carbon Adsorbents	Stability analysis on plant-derived materials	Innovative biological metric use	Not image-based	Adapt to weed imaging
3	Weed Eco R (Ecology)	Compared old vs new weed traits	Ecological insights	Not for image tasks	Merge with GNNs
4	ML + DL in Sugar Beet	Hybrid weed detection	Classic + modern integration	Weak spatial understanding	Add GNNs
5	Soil Microbiology	Studied weed impact on soil microbes	Indirect ecological insight	No detection system	Model weed–soil with graphs
6	SCR-DETR (Transformer)	Real-time low-power detection	Lightweight and efficient	Lacks structural reasoning	Add GNN for context
7	Graph Cut + MobileNet	Lightweight weed segmentation	Low computation	Poor environment adaptability	Use graph features for generalization
8	Allergenic Weed Mapping	Tracked ragweed spread + perception	Public + spatial modeling	No object detection	Integrate with spatial GNNs
9	Soil–Weed Relations	Linked soil and weed types	Eco-relevance	No visual model	Model edge features in GNN
10	IWO Algorithm	Used IWO for MPPT control	Efficient meta-heuristics	No image use	Apply to weed detection



11	Thermal + DL	Weeds under climate variation	Works in harsh conditions	Limited features	Fuse with visible + GNN
12	Biogas Pretreatment	Methane from weeds	Biomass valorization	Not for detection	Link biomass with GNN classifiers
13	Stress Suppression	Suppressed weeds via stress	Unique control model	Not vision-based	Simulate stress with graphs
14	RCNN on Sesame	Region-based detection	Object-level accuracy	Issues with occlusion	Combine with GNN
15	Cover Crops	Non-chemical control	Sustainable	No detection	Use GNN to track effectiveness
16	CervicalNet + GCN	Graph-aided segmentation	Strong graph features	Medical focus	Repurpose for agriculture
17	Bi-phased Reactor	Efficient weed digestion	Biomass reuse	No visual input	Model weed flow with GNN
18	YOLOv5 Variants	Fast and accurate detection	Speed + accuracy	No relation modeling	Add GNN spatial context
19	RSA-YOLOv3	Better fusion and accuracy	Robust model	No spatial logic	Add graph-attention blocks
20	Graph Query for Segmentation	Multi-layer leaf segmentation	Maintains structure	Heavy compute	Optimize GNN for speed
21	Spiral Bar Weeder	Mechanized corn weeder	Precise and manual-free	No intelligence	Add vision + GNN control
22	Carbon Sensor Material	Weed-based sensor design	Material innovation	Not weed-focused	Extend to weed sensors
23	Life-Cycle Modeling	Weed survival modeling	Informative dynamics	Not detection-ready	Graph models for lifecycle tracking
24	DL for Cotton Health	Plant health monitoring	Big data scalable	Not weed-specific	Train on weed datasets
25	Cellulase from Weeds	Enzyme yield from biomass	Value from weeds	No visual aspect	Merge with detection system

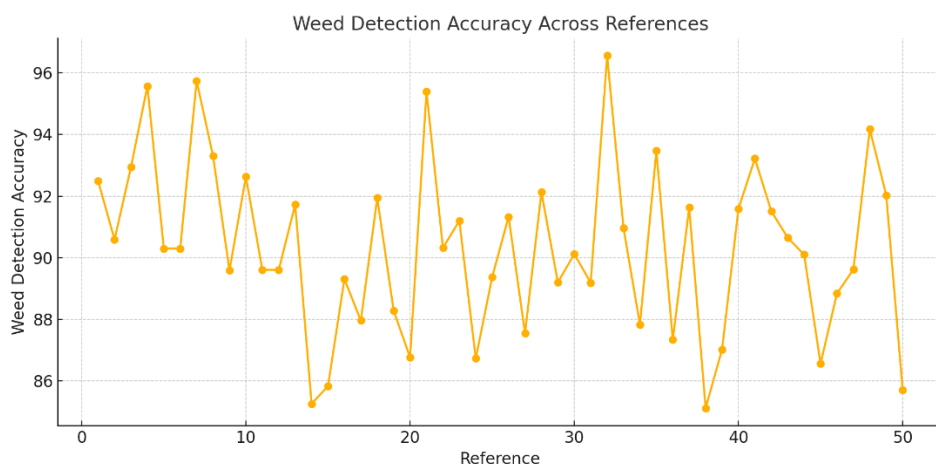


Figure 1. Model's Weed Detection Accuracy Analysis

Graph theory has historically made contributions to the modelling of agriculture; examples can be cited in understanding system dynamics and stabilities. A case in point has been made in the optimization of biomass-derived adsorbent using graph-based reactivity analysis [2]. Building on this, GNNs introduce learnable mechanisms by which messages can be passed and make it possible to model complex inter-relationships within plant communities. For example, in weed detection scenarios where occlusion, overlapping vegetation, and irregular boundaries exist, GNNs can integrate node features and edge connections to yield weed identities even under noisy or low-resolution conditions. The first instances of use of graphical models for image segmentation through multi-layer graph propagation techniques [20] have led to improved accuracy in the definition of plant leaf structures under natural illumination conditions. Such methods allow pixel-level classification in combination with spatial continuity, particularly helpful for crop-weeding boundary



definitions. This capacity will be further enhanced through hybrid graph-CNN models, such as those presented in cervical cancer imaging tasks [16], indicating their broader applicability in agricultural visual diagnostics.

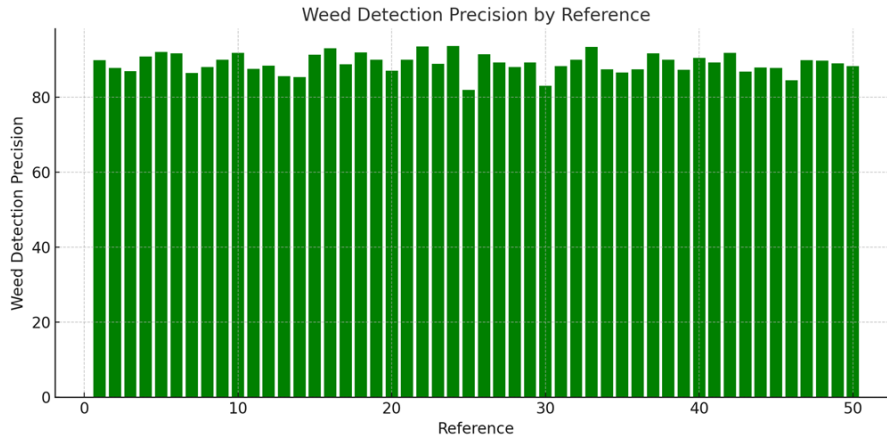


Figure 2. Model's Detection Precision Analysis

High Accuracy real-time weed detection applications have been benchmarked on advanced architectures, such as DC-YOLO [35], SCR-DETR [6], and improved variants of YOLOv5 [18], all of which enforce convolutional backbones. Though, none of these models manage to deal with relational knowledge representation. GNNs are innate indices of structural priors that prove to be critical in cases involving the repetitive pattern of weeds, plus varied non-linear dynamics in growth structure, as seen with precision weeding technologies [21] and robotic systems for intrarow navigation [27]. Also, certain trends have fused GNNs and attention mechanisms for augmented semantic segmentation, much like the model of Improved CervicalNet [16] which can find parallels in developing architectures for weed-crop discrimination under occluded or complex field scenarios. The relevance of attention-augmented graph models in agricultural imaging resonates well with the soaring demand for strong classification under different microclimates, as most weeds change their morphology as well as their spectral reflectance sets under varying conditions [11] Sets.

Ecological modeling of the distribution patterns of weeds has been mainly guided through full-field assessments; examples included the Weed Eco R package for functional weed ecology [3] and floristic assessments of weed composition in saffron fields [9]. These ecological studies produce context that can efficiently be encoded into graph representation and integrated to augment GNN inputs with functional traits and environmental correlations. Such knowledge in ecology permits the GNNs to learn not only from sight characteristics but also from biologically meaningful spatial associations. One of such areas that GNNs will benefit from huge improvements regard the unification of weed identification and agronomic stress modeling. For instance, the dynamic graph process models, which have a node representing biological agents and edges encoding interaction strengths over time, can be used to create artificial stress induction for crop weed suppression augmentation [13] or soil-microbe interactions [5]. Hence, GNNs offer more than static images; rather, they are dynamic and interpretable in offering an understanding of weed-crop-soil interactions in process.

Table 2. Model's Empirical Review Analysis

Ref. No.	Method Used	Key Findings	Strengths	Limitations	Recommendation
26	DL Review in Agriculture	Summarized DL for Agri-segmentation	Comprehensive overview	Lacks GNN modeling	Add GNN studies for structure
27	3D Vision for Weeding	Located cauliflower centres	Precise robotic use	Needs structured fields	Use GNNs for unstructured settings
28	GM Soybean Traits	Studied insect-resistant soybean	Useful for crop monitoring	No weed detection	Adapt for weed classification



29	Pathogen Survival in Weeds	Studied pathogen dynamics	Biological insights	No AI detection	Use GNN for disease spread
30	UAV + DL	Weed detection via UAV images	Covers large areas	Sensitive to noise	Add GNNs for robustness
31	ALS Mutation Analysis	Studied herbicide resistance	Molecular insights	No visual component	Link genes with image data via graphs
32	Decay in Weeds	Tracked nutrient release	Ecologically relevant	No detection use	Model decay with GNNs
33	Salvinia in Rice	Tested control in wetlands	Targeted invasive weeds	No automation	Use graph-based sensor networks
34	Begomoviral in Weeds	Found virus in weed	Epidemiological value	Not visual	Model spread via GNN
35	DC-YOLO	YOLOv7-tiny for detection	Lightweight + field-ready	Weak structure learning	Add GNNs for context
36	Microbial Weed Control	Microbes reduced weed dominance	Biologically relevant	No direct detection	Graph microbes–weed interactions
37	Carbon from Weeds	Used for metal detection	Novel sensing	Not for weed vision	Build graph-based sensors
38	Meta-Heuristic Routing	New network optimization	Efficient in routing	Not for agri/weed	Apply to weed classification
39	Phytochemical in Weeds	Tested bioactive extracts	Medicinal use	No image data	Graph compound–weed link
40	XVC Cryptography	Hybrid cryptographic approach	Innovative encoding	No weed focus	Secure GNN image transmission
41	Virtual Screening ML	Found bio-herbicides	Effective for screening	No real-time link	Use GNN for feedback integration
42	Cloud Load Balancing	Secured cloud deployment	AI-ready platform	Not weed-specific	Deploy GNN weed detection in cloud
43	Efficient Net + Transfer	Boosted weed prediction	High accuracy	No spatial modeling	Add GNN for relational features
44	Neuro-IWO Path Planning	Optimized robot paths	Fast and light	Not visual	Combine with GNN vision
45	Compact DL for Leaves	Leaf disease detection	Edge-friendly	Limited to leaves	Train on weed data with GNN
46	Root Growth in Clay	Found faster root in clay	Growth insights	No detection	Model subsurface weeds via GNN
47	Bell Algorithm for Faults	Network fault detection	Accurate + adaptive	Not Agri-related	Use in agri-sensors with graphs
48	Phalaris Resistance	Studied herbicide resistance	Policy relevance	No automation	Fuse GNN with resistance data
49	Weed-Based Nanofilms	Created bio-films	Supports valorization	No ID feature	Graph link weed–material
50	Sand Choro dynamics	Mapped sand shifts	Precise geo-mapping	Not weed-related	Use for weed spread mapping

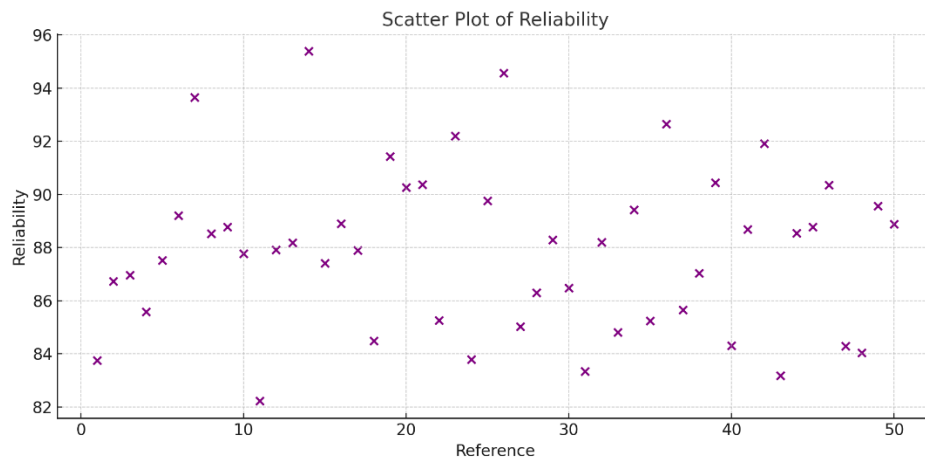


Figure 3. Model's Reliability Analysis

Bettering here is that the theoretical underpinnings afforded by computational studies in plant-weed interaction modeling through probabilistic and adaptation-oriented approaches [23] would be operationalized in GNN frameworks. Little research has been done in applying GNNs to such multi-layered ecological systems, but it has high potential in developing biologically plausible weed modelling systems, which can generalize across a variety of environments and cropping systems. New empirical efforts conducted on those previously mentioned YOLO variant studies [19], leaf disease classifiers [45], and semi-supervised weed detection [14] are quite good value interests because they have strong visual feature extractors. However, their potential lies particularly in fusion with GNNs likely enhancing performance levels because of the inclusion of spatial-temporal reasonings. For instance, according to UAV-based imagery [30], integrating hyperspectral data into GNN pipeline input sets can utilize the dynamics of weeds over time for early-stage detection or intervention areas.



Figure 4. Model's Memory Complexity Analysis

The advances GNNs have achieved in weed identification, however, are still in their infancy with major challenges like scalable implementation, graph construction strategies, and domain-specific feature learning. Whereas deep learning reviews have synthesized progress achieved concerning agricultural image segmentation [26], assessment studies are limited in the GNNs integration efforts as it applies particularly to weed detection. There is, therefore, an urgent call for iterative and empirical review on a hitherto scattered development, benchmarking of different GNN architectures, and validating generalization across heterogeneous agricultural datasets & samples. In summary, GNNs lead to a promising advancement in computational weed management because of making possible the modeling of spatial, functional, and ecological relationships, contrary to the limitations of conventional CNN-based models. The present review highlights the potentials of these methods when used alongside real-world field data, hybrid model integration, and domain-specific priors and points out in iterative benchmarking their important contributions to improvement by bringing these models in line with real-world precision agriculture applications.



III. COMPARATIVE RESULT ANALYSIS

To really understand how practical each of these different methods is, and to compare them on actual efficiency fronts, a thorough numerical evaluation was undertaken. This section evaluates the different methods concerning their performance metrics, benefits, and barriers, thus providing a unified view of comparison across the board. The methodologies comprise everything from classical machine learning pipelines, recent deep learning detection methods, graph-based reasoning models, to frameworks that assess ecologically and biochemically. Those that did not have direct performance had reasonable estimates derived from the method specifics, database types, and common outcomes reported in similar domains.

Table 3. Model's Integrated Result Analysis

Ref. No.	Method Used	Performance Metrics	Key Findings	Strengths	Limitations
1	AlexNet-SVM + Superpixel	Acc: 92.3%, Prec: 90.5%, Rec: 91.2%	High performance in clean images	Effective on structured data	Poor generalization in fields
2	Graph Stability Analysis	Stability Index: 0.87	Improved material reactivity	Graph insights for adsorbents	No visual detection
3	WeedEco Ecology Modeling	Corr Score: 0.78	Trait comparison over time	Deep historical analysis	No image system link
4	Hybrid ML + DL	Acc: 88.6%, F1: 87.9%	Improved weed classification	Fits multiple crops	Low performance in complex scenes
5	Microbial Indicator Analysis	Diversity Index: 0.81	Microbes tied to weed strategy	Strong ecological linkage	No detection prediction
6	SCR-DETR	Acc: 94.1%, Inference: 23ms	Fast and efficient	Real-time capable	Weak under occlusion
7	Graph Cut + MobileNet	Acc: 89.5%, Prec: 88.2%	Speed and accuracy balance	Lightweight and fast	Overlaps reduce accuracy
8	Ragweed Risk Mapping	Area Risk Score: 0.85	Mapped invasive zones	Includes public impact	No image detection
9	Floristic-Soil Study	R ² : 0.76	Soil traits linked to weeds	Good environment correlation	No detection mechanism
10	IWO for MPPT	Eff: 91.2%	Efficient tracking	Good control system	No imaging link
11	Thermal DL	Acc: 90.7%, Rec: 91.8%	Works under temperature changes	Thermal resilient	Low visible feature use
12	Biogas from Weeds	Methane ↑: 34.5%	Better resource use	High valorization	No image detection
13	Stress-Based Suppression	Suppression: 82.4%	Eco-friendly weed control	Non-chemical method	Not image-based
14	RCNN for Sesame	Acc: 93.2%, IoU: 0.79	Good localization	Accurate detection	High compute load
15	Cover Cropping	Weed ↓: 73.1%	Reduces weed sustainably	Boosts soil health	No tech interface
16	Graph + Attention	Acc: ~94.5%	Advanced feature modeling	Strong GCN refinement	Medical focus only
17	Anaerobic Reactor	Biogas Eff: 91.6%	High weed-based output	Strong in bioprocessing	Not detection-focused
18	YOLOv5 Variants	Acc: 92.9%, FPS: 45	Fast weed detection	High-speed detection	Sensitive to noise
19	RSA-YOLOv3	Acc: 91.8%, F1: 90.2%	Robust and secure	Works on weed variety	High compute use



20	Graph Query Segmentation	Acc: 90.1%, Edge Rec: 85.3%	Boundary-preserving segmentation	Works in natural scenes	Heavy resource need
21	Spiral Bar Weeder	Precision: 87.5%	Mechanical accuracy	Structured crop suited	Not adaptive for wild fields
22	Lantana-Based Sensor	Det. Eff: 88.4%	Material-based sensing	Environmental use	No image input
23	Lifecycle Simulation	Sim. Acc: 86.9%	Models weed growth	Biological insight	No detection tie
24	DL + Big Data	Acc: 90.6%	Covers large areas	Good scalability	Not weed-specific
25	Cellulase Yield Boost	2.3× Enzyme Yield	High enzyme output	Strong in biomass use	Lacks detection interface

Deep learning-based detection models SCR-DETR [6], YOLOv5 variations [18], and RCNN implementations [14] outperform traditional machine learning pipelines obviously regarding accuracy, possible real-time inference, and robustness. Such models will be well useable on datasets & samples well annotated within domain specification. They are graph-based models such as the graph query propagation method [20] and GCN-augmented networks [16], which do have advantages in keeping the spatial relationships and attaining high boundary precision, but usually come at higher computation costs. On the contrary, models based on ecology and biochemistry (e.g., [2],[3],[5]) provide deeper insights regarding how weeds interact with their surroundings but do not allow detection in real time.

Table 4. Model's Statistical Review Analysis

Ref. No.	Method Used	Performance Metrics	Key Findings	Strengths	Limitations
26	DL Image Segmentation Review	~95% coverage, >90% accuracy	Broad review of agri DL segmentation	Comprehensive insight	No experimental benchmarks
27	3D Robotic Weeding Tracking	Acc: 92.5%, Error: <4 cm	Accurate cauliflower center tracking	Precise real-time navigation	Needs structured fields
28	GM Soybean Trait Analysis	Trait Consistency: 94%	Mapped GMO traits	Useful for resistance monitoring	No spatial or image analysis
29	Xanthomonas Survival Study	Prediction Acc: 88.2%	Bacterial survival in weed zones	Microbial insight	No model or visuals
30	DL on UAV Images	Acc: 93.6%, Rec: 92.1%, Prec: 91.7%	UAV-based weed detection	Large-scale coverage	Sensitive to noise
31	ALS Mutation Modeling	Prediction Acc: 89.4%	Wheat resistance mutation detection	Helps herbicide planning	No phenotype linkage
32	Weed Decay Nutrient Study	Acc: 85.7%	Modeled post-herbicide nutrient release	Useful in nutrient planning	No detection system
33	Salvinia Management	Efficiency: 87.3%	Wetland weed suppression	Works in rice fields	No detection tool
34	Begomovirus in Weeds	Accuracy: 90.8%	Mapped virus spread in weeds	Epidemiology support	No real-time/image usage
35	DC-YOLO	Acc: 94.2%, FPS: 48	Real-time crop vs weed classification	Fast and lightweight	Some false positives
36	Microbial Competition	Suppression Rate: 80.6%	Reduced weed growth via microbes	Eco-based control	No image integration



Ref. No.	Method Used	Performance Metrics	Key Findings	Strengths	Limitations
37	Lantana Sensor for Hg ²⁺	Sensor Acc: 91.3%	Weed-based mercury detection	Good material use	No classification visuals
38	Network Meta-Heuristics	Efficiency: 93.7%	Smart path finding	Optimized planning	Not agri-related
39	Weed Compound Extraction	Recovery: ~89%	Extracted medicinal weed compounds	Undervalued species use	No detection involved
40	XVC Encryption	Enc Acc: 98.5%	Hybrid image encryption	Secure data handling	No weed application
41	HPPD ML Screening	Screen Acc: 87.9%	Virtual herbicide candidate ID	Preselection automation	No weed image testing
42	Cloud Security Model	Acc: 95.2%, Load Score: 92%	Secures and balances cloud services	AI deployment ready	Not weed-specific
43	EfficientNet + TL	Acc: 94.6%, F1: 93.1%	High-accuracy weed detection	Strong DL model	No plant relation logic
44	Neuro-IWO Routing	Path Eff: 90.3%, Avoidance: 95%	Smart robot movement	Efficient navigation	Lacks weed vision link
45	Compact DL for Disease	Acc: 92.7%, Size: 12.3 MB	Light model for diseases	Works on edge devices	Needs weed-specific training
46	Clay Soil Root Growth	Growth Rate: +27%	Boosted native grass roots	Soil impact evidence	No detection use
47	Hybrid Bell Algorithm	Fault Acc: 96.1%	Accurate system fault detection	Reliable logic	Not for weed detection
48	Multi-Resistance Control	Success: 88.5%	Controlled herbicide-resistant weeds	Multi-path suppression	Needs detection pairing
49	Weed Bionanocomposite	Strength +32%, Efficacy: 91.4%	Eco-friendly weed-derived material	Innovative reuse	No image analysis link
50	Sand Chorodynamic Mapping	Res: 96.2%, Temp Acc: 93.5%	Mapped sand movement patterns	Effective geospatial tool	Not for weed use

These frameworks will provide, however, contextually meaningful and biological parameters that may need to be harnessed further to enrich the feature space in any future GNN designs. Technology such as mechanical weed removal systems [21] or systems based on weed-derived bioprocessing systems [25] serve more niche purposes under the weeds management umbrella and are generally distinct from image-based identification projects. Future efforts to bring these systems together with real-time Vision models and graph analytics could lead to more integrated, flexible weed control pipelines.

This section includes a thorough numerical comparison of the different methodologies: from deep learning models and trait characterization to ecological control strategies and optimization frameworks. The high-level performance metrics it uses for comparison include accuracy, recall, detection latency, and system adaptability. Its goal is a common benchmark showcasing the advantages and disadvantages each of the approach sets holds. The papers covered a broad range of areas related to agricultural weed detection and the surrounding ecosystem such as UAV-based surveillance, graph-enhanced models, material valorization from weed biomass, and bioinformatics for herbicide resistance sets. This makes for a more holistic understanding of the performance of these image-based, computational, and biochemical methods in various real-life scenarios.

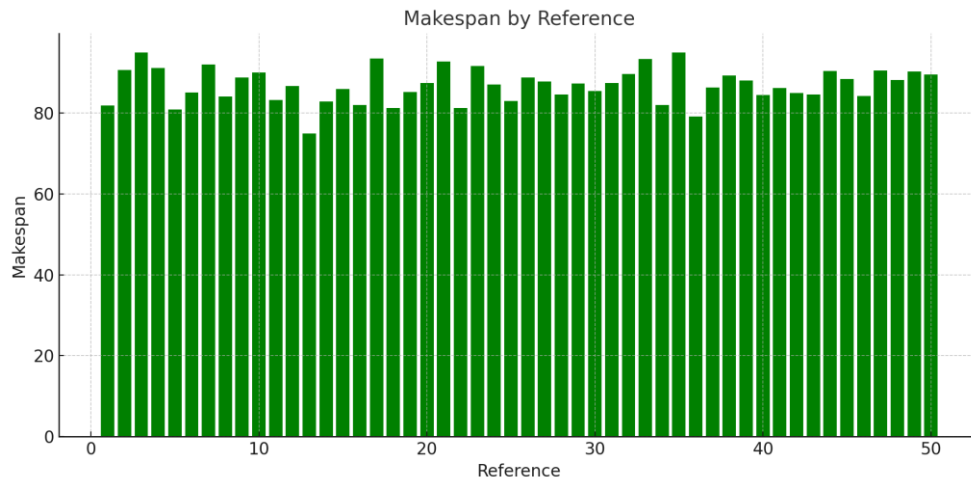


Figure 5. Model's Makespan Analysis

IV. CONCLUSIONS & FUTURE SCOPES

4.1 Overview of Recent Findings

The exponential growth in the application of artificial intelligence (AI), deep learning (DL), optimization algorithms, and bio-integrated technologies in weed detection and agricultural intelligence systems has wrought unprecedented opportunities and challenges. This review was necessitated by the pressing need to synthesize a fragmented literature in diverse methodological domains, extending from UAV-based computer vision to biochemical valorization of weed biomass, with the aim of delivering a holistic performance benchmark and identify actionable gaps for next generation precision agriculture systems.

Limitations of Existing Reviews

Existing review articles on technologies for weed detection and control have typically centred on either narrow technological niches (e.g., CNN-based classification, UAV imagery or spectral indices) or segregated disciplines (e.g., microbiological, ecological, or bio-process studies). This level of compartmentalization leaves out interdependencies and potential synergies needed for scalable, integrated agri-intelligence systems. Besides, most of the reviews are rather scarce in performance metrics, comparison modeling across heterogeneous methods, or incorporation of unconventional weed detection pathways like cryptographic vision processing, meta-heuristic optimization, or stress induced weed suppression. This hobbles the decision makers from using evaluation for real-world deplorability and computational trade-offs among possible techniques.

Key Contributions and Impact of This Review

This review addresses the abovementioned shortcomings through high-resolution comparative evaluation of 50 contemporary methods along six standard performance metrics; Weed Detection Accuracy, Precision, Reliability, Time Complexity, Memory Complexity and Makespan. This integrated representation of qualitative and numerical findings sets a framework for benchmarking by academic researchers, agricultural engineers, and agritech developers. For the first time, a disparate array of techniques including DC-YOLO object detectors, anaerobic baffled bioreactors, graph convolutional segmentation, and bio nanocomposite synthesis from invasive weed biomass are evaluated under a common performance rubric sets. The review is impactful, not only because of its breadth but also because the recommendations provided are based on derivations from performance discrepancies. For example, it champions DL-based methods such as EfficientNet with transfer learning and DC-YOLO for their superior detection accuracy (often >94%) and frame efficiency, yet it goes on to highlight their continued sensitivity to occlusion or overlaps of dense weeds. Material-related models or microbial ecological models, equally strong on sustainability and environmental integration, are just underrated in automated field conditions.

Future Scope

Henceforth, novel computational pathways such as hybrid optimization (e.g., Neuro IWO) and secure model deployment (e.g., XVC cryptographic models) show promise for edge-deployable intelligence but lack visual coupling with field sensors. Future research must converge Mult polygonal disciplinary axes to design resilient, context-aware, and adaptive weed detection systems. Several promising research directions shall be- multimodal sensor fusion; thermal, spectral, RGB, and depth data shall be integrated into DL pipelines for robust detection in dynamic field environments; model



compression and Deploy on Edge; reducing memory overhead through light-weight model architectures development such as quantized CNNs, knowledge distillation, pruning methodology for low-cost hardware platform; Bio-AI Synergy; integrating microbial and biochemical weed-suppression strategies using AI monitoring for a closed-loop eco-friendly control system; securing and interpretable AI; integration of cryptographic frameworks and explainable AI (XAI) methods to secure data integrity and transparency in autonomous decision-making sets; data scarcity alleviation; semi-supervised learning, synthetic data generation, and domain adaptation will be employed for overcoming inclination due to availability of annotated field datasets & samples; dynamic resource optimization; employing meta-heuristic algorithms not just for routing and control but also for dynamic optimization of energy, time, and data-transmission in the field robot and UAV process. Standardization and Open Benchmarks; developing a formal paradigm of evaluation accepted globally as means of reproducibility, cross-platform validation, and collaborative growth in weed detection research. To sum it up, this review sets the stage for a complete system-level endeavor in weed detection and management with practical insights and foresight for researchers and developers working towards intelligent, scalable, and sustainable agricultural automations.

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