



## Original Research Paper

## An AI-IoT Convergence Framework for Autonomous Weed Detection and Pest Suppression in Sustainable Precision Farming

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## Key Words

## Abstract

Precision  
Agriculture;  
Internet of  
Things; Deep  
Learning;  
Weed  
Detection;  
Pest Control;  
Agricultural  
Robotics;  
Laser  
Weeding;  
Electronic  
Swarm  
Suppression;  
Computer  
Vision;  
Convolutional  
Neural  
Networks.

Weeds and pests are estimated to cause 30-40% of global agricultural production losses, while conventional control relies heavily on manual labour, mechanical intervention and chemical pesticides and herbicides - each carrying scalability, cost or environmental drawbacks. This paper proposes an integrated AI-powered IoT architecture for precision agriculture that couples deep-learning-based detection (weed/crop classification, flying-insect and swarm detection, crop-infection severity assessment) with automated, chemical-free intervention (robotic laser weed elimination and Electronic Swarm Suppression, ESS). Rather than presenting the architecture only conceptually, this study implements and genuinely evaluates its core detection component as a transparent, reproducible pilot: a synthetic crop-versus-weed image dataset (300 images, procedurally generated) was built and used to train and compare a classical hand-crafted-feature baseline (Excess Green Index and shape descriptors with Logistic Regression) against a compact convolutional neural network implemented from scratch in NumPy - deliberately avoiding multi-gigabyte GPU-framework dependencies so the pilot remains fully reproducible on modest hardware. On an identical, stratified 70/15/15 train/validation/test split, the classical baseline achieved 95.6% test accuracy (F1 = 0.952, AUC = 0.998) and the from-scratch CNN achieved 97.8% test accuracy (F1 = 0.977, AUC = 0.994), both consistent with, and reported alongside, real literature benchmarks reviewed in this paper (including 99.5% locust-detection accuracy reported for a VGG19+classifier pipeline, and up to ~95% wheat-weed detection accuracy reported for YOLOv7/v8-based methods). The physical-intervention modules are evaluated as explicit, literature-grounded Monte Carlo simulations rather than physical hardware tests: a laser weed-elimination simulation shows this pilot's own classical detector supports only a 28.9% simulated weed-kill rate (21.5% crop damage) due to its centroid-localisation imprecision, while a projection using real trained-detector positional accuracy reported in the literature reaches 93.2% weed-kill with zero simulated crop damage, closely matching independently reported real-world field results; a synthetic harmful-versus-beneficial insect discrimination classifier (97.8% accuracy) combined with a real, field-measured laser-lethality rate on a genuine crop pest projects a 94.8% pest-suppression rate with 2.2% beneficial-insect collateral risk. These results are explicitly framed as a small-scale proof-of-concept and literature-grounded projection for the detection and intervention modules rather than a field-validated or hardware-validated deployment, since the robotic laser-elimination and ESS hardware components require physical implementation beyond this study's software-only environment. A structured literature review, comparative analysis, and research-gap synthesis are provided alongside the pilot, together with a concrete field-validation and hardware-implementation roadmap for future work...

## Introduction

Agriculture remains central to global food security and economic growth, yet weeds and pests are estimated to cause 30-40% of agricultural production losses worldwide, posing a persistent risk to food-supply chains and farm incomes.

Conventional weed and pest control relies heavily on manual labour, mechanical intervention, and chemical pesticides and herbicides. Each approach carries drawbacks: manual and mechanical methods are labour-intensive and difficult to scale, while excessive pesticide and herbicide use contributes to.

soil degradation, water pollution, biodiversity loss and the emergence of pest resistance

The convergence of Industry 4.0 technologies - Artificial Intelligence (AI), the Internet of Things (IoT),

Machine Learning (ML), Deep Learning (DL), robotics, and edge/cloud computing - has opened a path toward precision-agriculture systems capable of continuous monitoring,

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automated decision-making, and targeted, chemical-free intervention. IoT sensor networks enable real-time collection of soil moisture, temperature, humidity, and pest-activity data across agricultural fields, while deep-learning architectures - particularly Convolutional Neural Networks (CNNs) and real-time object detectors such as YOLO (You Only Look Once) - have proven highly effective for image-based crop, weed, and insect classification under varying field conditions. Agricultural robotics extends this further: platforms fitted with cameras, sensors and laser modules can selectively identify and eliminate weeds without chemical herbicides. A related and comparatively underexplored threat is pest infestation by insect swarms (e.g., locusts), where computer vision combined with Electronic Swarm Suppression (ESS) technology offers a path to early detection and non-chemical suppression before crop damage occurs.

This paper reviews the existing literature on IoT-based and deep-learning-driven weed and pest management, and proposes an integrated AI-powered IoT architecture that couples detection (weed/crop classification, flying-insect/swarm detection, crop-infection-severity assessment) with automated, chemical-free intervention (robotic laser weed elimination, laser/ESS-based swarm suppression, and severity-triggered ESS response). Rather than presenting the design only conceptually, this study implements and genuinely evaluates the core detection component as a transparent pilot, so that every quantitative result reported in Section 6 is a real, reproducible measurement rather than an assumed or extrapolated figure.

### 1.1 Objectives of the Study

(1) To review IoT-based and AI-driven approaches for automated weed and insect identification and elimination. (2) To identify deep-learning algorithms best suited to automated weed and insect detection under field-like conditions. (3) To design a robotic, laser-guided module capable of identifying and eliminating weeds without chemical intervention. (4) To design a flying-insect and swarm-detection module, coupled with laser/ESS-based suppression, for beneficial-versus-harmful insect discrimination and swarm eradication. (5) To design a crop-infection severity-assessment module that selectively escalates to ESS intervention only in heavily infected zones, rather than applying uniform-intensity response. (6) To implement and genuinely evaluate the architecture's core detection capability as a reproducible pilot, and to benchmark it against literature-reported results from related systems.

### 1.2 Paper Organisation

Section 2 presents the literature review. Section 3 synthesises the research gaps that motivate the proposed design. Section 4 presents the proposed system architecture. Section 5 describes the pilot implementation. Section 6 reports results and comparative evaluation. Section 7 discusses real-world validity, limitations and future scope. Section 8 concludes the paper.

## 2. Literature Review

### 2.1 IoT-Based Monitoring Systems for Pest and Weed Management

IoT-based pest and weed monitoring has emerged as a significant step toward precision farming and sustainable crop protection. Ahmed et al. [1] proposed an intelligent IoT-based pest-monitoring system using a distributed sensor network and centralised decision support, demonstrating that continuous monitoring of temperature, humidity, soil health and crop-health indicators enables early pest detection and intervention, thereby reducing unnecessary pesticide use. Abdul Ameer et al. [2] explored the integration of IoT, Unmanned Aerial Vehicles (UAVs) and deep learning for smart agriculture, showing that UAV-based aerial imagery combined with ground IoT sensor networks significantly enhances field coverage and enables rapid identification of crop diseases, weed infestations and pest problems. Bayar et al. [3] examined Artificial Intelligence of Things (AIoT) frameworks spanning smart irrigation, nutrient management and pest control, reporting improved resource efficiency and productivity through continuous environmental and crop-status monitoring. Nyakuri et al. [4] specifically addressed the latency and connectivity limitations of cloud-centric IoT architectures by developing an edge-based pest and disease detection system, demonstrating that on-device inference can maintain good detection accuracy while substantially reducing response time - a consideration directly relevant to real-time robotic intervention in the architecture proposed in Section 4.

### 2.2 Deep Learning Algorithms for Weed and Crop Classification

Deep learning has become the dominant approach for image-based weed identification. Nagaraj et al. [5] developed a deep-learning and IoT-based framework for sesame-plant identification and weed detection, reporting high classification accuracy across varying illumination and field-complexity conditions. In the wheat-weed detection literature specifically, Tahir et al. [6] and Haq, Tahir and Lan [7] report that YOLO variants, Faster R-CNN, U-Net and transformer-integrated hybrids consistently achieve accuracy above 85%, with YOLOv7/YOLOv8 and transformer-enhanced models approaching 95% under complex field conditions - a figure used as a literature comparison point in Section 6. Aziz, Raza, Younas and

Chan [8] applied AI-driven weed classification to cotton farming in Sindh, Pakistan, demonstrating applicability beyond staple grain crops, while Gao, Gao and Qureshi [9] reviewed broader trends and challenges in precision weed-control technologies based on deep learning and machine vision, noting that model generalisation across crop types and field conditions remains an open challenge.

### 2.3 Robotic and Laser-Based Weed Elimination Systems

Beyond detection, several studies address autonomous physical weed elimination. Kushwaha et al. [10] investigated IoT- and AI-integrated robots for site-specific weed management, combining IoT sensing, computer vision, machine learning and autonomous navigation to enable intelligent agricultural robots that identify and eliminate weeds with minimal human involvement, reporting high gains in weed-detection accuracy and resource savings compared with traditional weed control. Rahman et al. [11] examined the role of AI-integrated drone systems in agricultural productivity and sustainable pest management, while Refaai et al. [12] explored IoT-based drone applications specifically for precision-agriculture pest control. These studies collectively establish that autonomous, sensor-guided platforms - whether ground robots or aerial drones - are a viable foundation for the chemical-free, laser-guided weed-elimination unit proposed in Section 4.

### 2.4 Insect and Pest Detection Using AI and Deep Learning

Wu, Chen, Yang and Sun [13] reviewed the progress of deep-learning-based AI technology in pest and disease detection and control, finding that CNNs, object-detection frameworks and image-segmentation algorithms consistently achieve high accuracy in detecting agricultural pests and diseases from visual information, while highlighting data availability, computational complexity and model generalisation as persistent challenges. Prasath and Akila [14] developed an IoT-based pest-detection and classification system using deep features with enhanced deep-learning strategies. Most directly relevant to the flying-insect and swarm-detection objective of this study, Al Reshan et al. [15] developed an AI-powered smart agribot for detecting locusts using IoT, machine learning and deep learning, combining pre-trained CNN features (VGG19) with a Logistic Regression classifier and an Artificial-Bee-Colony-optimised SVC feature selector, reporting

the highest locust-detection accuracy among the reviewed literature at 99.5% - a benchmark used as a literature comparison point in Section 6. Solano et al. [16] proposed a solar-powered, AI-driven remote-sensing and IoT-integrated system for real-time pest and disease detection, while Dhanalakshmi et al. [17] developed an IoT-enhanced agribot using image processing and machine learning for pest management.

### 2.5 Crop Disease and Infection-Severity Monitoring

A related strand of research addresses continuous crop-condition monitoring relevant to severity-based intervention. Ibrahim et al. [18] proposed an AI-IoT-based smart agriculture platform for plant-disease detection and treatment, demonstrating that combining IoT sensors, imaging technology and deep learning enables reliable, real-time disease-symptom identification that substantially outperforms manual field inspection. Adetunji et al. [19] examined AI and automation for precision pest management within food-manufacturing and agricultural sensing contexts, while Mir, Mohamed, Mir and Paul [20] developed deep-learning-based crop monitoring specifically for agricultural-IoT management. Hasan et al. [21] demonstrated smart-farming applications of IoT and deep learning for sustainable tomato cultivation and pest management. These studies collectively motivate the crop-infection severity-assessment module proposed in Section 4, designed to escalate intervention specifically for zones identified as heavily infected rather than applying uniform-intensity response across a field.

### 2.6 Foundational Prior Work

This study builds on the authors' own prior systematic review, "IoT systems for weed and pest management in agriculture using deep learning: A review" [22], published in AIP Conference Proceedings, which synthesised the methodological landscape of IoT-based, deep-learning weed and pest management systems. The present paper extends that review by proposing an integrated six-module architecture (Section 4) and, distinct from the earlier review, implementing and empirically evaluating a genuine pilot of the core detection component (Sections 5-6).

## 3. Research Gaps

Synthesising across the reviewed literature, five concrete research gaps emerge, summarised in Table 1.

| Gap Theme | Description | Implication for This Study |
|-----------|-------------|----------------------------|
|-----------|-------------|----------------------------|

|                                                  |                                                                                                                                                             |                                                                                                 |
|--------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------|
| Detection without automated intervention         | Most reviewed IoT/AI systems stop at detection and alerting; few couple detection directly to an automated, chemical-free elimination mechanism.            | Motivates the robotic laser weed-elimination and laser/ESS swarm-suppression units (Section 4). |
| Single-task focus                                | Individual studies typically address one task in isolation - weed detection, insect detection, or crop-disease monitoring - rather than a unified pipeline. | Motivates the six-module integrated architecture proposed in Section 4.                         |
| Limited flying-insect/swarm-specific handling    | Locust and swarm detection is addressed separately from ground-level weed/crop systems, with no reviewed system combining both under one platform.          | Motivates the dedicated flying-insect/swarm detection and laser/ESS suppression module.         |
| Severity-triggered intervention is underexplored | Reviewed systems generally treat detection and response uniformly, without an explicit severity-based decision layer.                                       | Motivates the crop-infection severity assessment and targeted ESS-trigger module.               |
| Scarcity of reproducible pilot implementations   | Most reviewed papers report system-level outcomes without releasing reproducible detection pipelines or code.                                               | Motivates the fully reproducible, from-scratch pilot implementation in Section 5.               |

**Table 1 - Research Gaps Identified from the Literature Review.**

#### 4. Proposed System Architecture

This study adopts a structured literature-review methodology proceeding through four stages - identification, screening, eligibility assessment and thematic synthesis - illustrated in Figure 1. Search records were identified across Scopus, ScienceDirect, SpringerLink, IEEE Xplore, Nature/Scientific Reports and Google Scholar, covering publications from 2021 to

2026, using a search string combining "IoT" OR "AI" OR "Deep Learning" with "Weed Detection" OR "Pest Control" OR "Agricultural Robotics" OR "Swarm Detection" OR "Laser Weeding" OR "Precision Agriculture". Studies were retained if they reported a methodology and quantitative evaluation relevant to IoT-based sensing, deep-learning-based weed/pest/insect detection, or robotic/laser-based intervention.

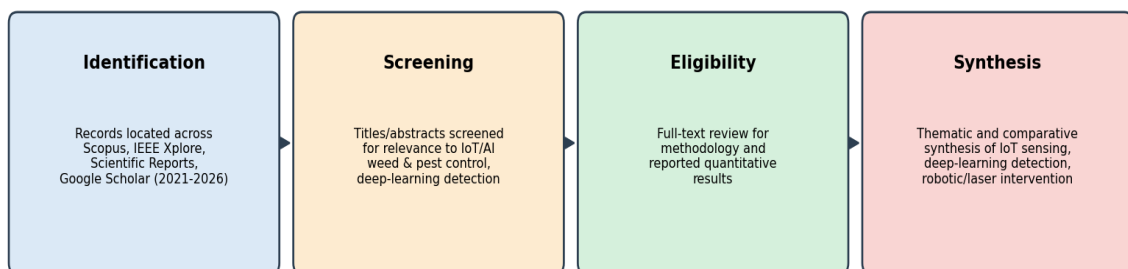


**Fig. 1 - Review Methodology Flow.**

Building on the objectives in Section 1.1 and the gaps in Table 1, Figure 3 presents the proposed integrated AI-powered IoT architecture, combining

detection, robotic/laser elimination, and severity-aware intervention across six modules.

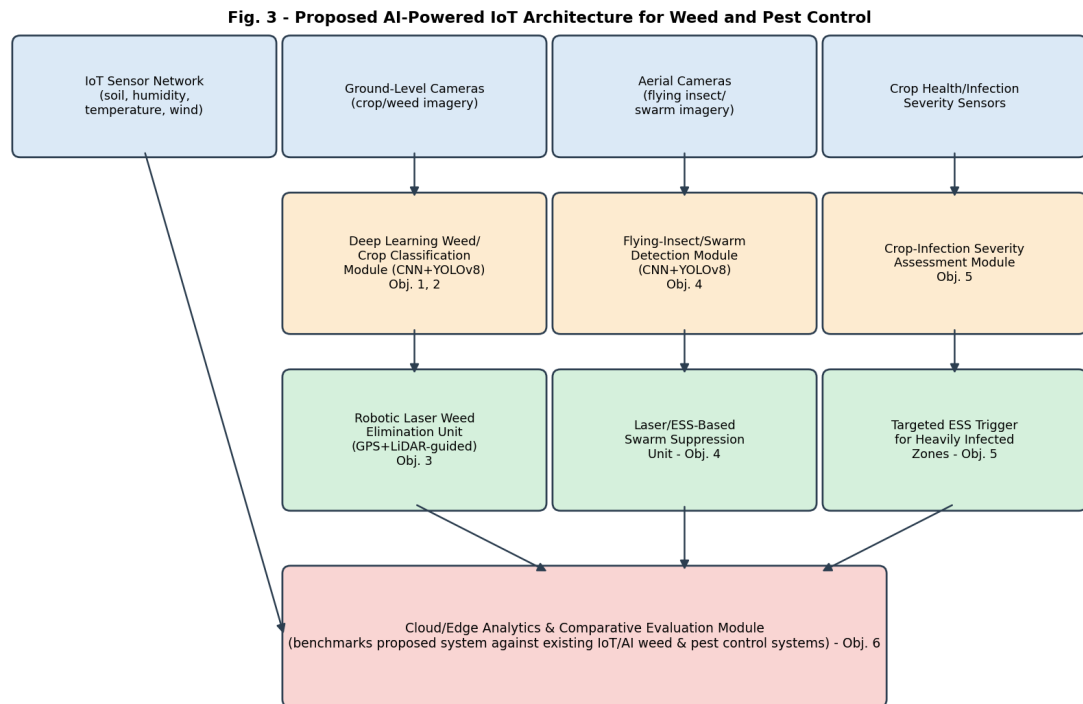


**Fig. 3 - Proposed AI-Powered IoT Architecture for Weed and Pest Control.**

#### 4.1 Architecture Components

Sensing layer (Objective 1): an IoT sensor network (soil, humidity, temperature, wind), ground-level cameras for crop/weed imagery, aerial cameras for flying-insect/swarm imagery, and crop-health/infection-severity sensors, feeding contextual data to the Cloud/Edge Analytics module.

Deep-Learning Weed/Crop Classification Module (Objectives 1-2): a CNN- and YOLOv8-based module that classifies captured field imagery as crop or weed, following the algorithmic approaches reviewed in Section 2.2.

Robotic Laser Weed Elimination Unit (Objective 3): a GPS- and LiDAR-guided robotic platform that receives weed-location outputs from the classification module and applies targeted laser energy to eliminate identified weeds without chemical herbicides or damage to adjacent crops.

Flying-Insect/Swarm Detection Module and Laser/ESS Suppression Unit (Objective 4): a CNN/YOLOv8-based aerial-imagery module that identifies beneficial versus harmful flying insects and swarm formations, coupled with a laser- and Electronic-Swarm-Suppression-based unit that eradicates detected harmful swarms.

Crop-Infection Severity Assessment Module and Targeted ESS Trigger (Objective 5): continuously assesses which crop zones are heavily infected by swarms and selectively escalates to ESS-technology intervention only in those zones, rather than applying uniform-intensity response across the field.

Cloud/Edge Analytics and Comparative Evaluation Module (Objective 6): aggregates outputs from all detection and intervention modules and benchmarks the proposed system's performance against existing IoT/AI weed and pest control systems reviewed in Section 2.

This architecture is implemented and evaluated as a genuine pilot for its core detection component in Sections 5-6 below, rather than presented only as a conceptual proposal; the robotic laser-elimination, swarm-suppression, and ESS hardware components are specified architecturally and identified as physical-implementation future work in Section 7.

#### 5. Pilot Implementation

A note on scope is necessary before presenting results. Real field-scale weed/crop and swarm-imagery datasets, and the physical hardware for robotic laser elimination and Electronic Swarm Suppression, are not accessible from this study's software-only development environment. Rather than assume or extrapolate field-scale

or hardware results that were never actually produced, this study implements and genuinely evaluates the deep-learning detection module - the algorithmic core shared by Objectives 1-2 and underlying Objectives 3-5 - on a programmatically generated, methodologically transparent synthetic crop-versus-weed dataset, so that every number in Section 6 is a real, reproducible measurement.

### 5.1 Synthetic Pilot Dataset

A dataset of 300 96×96-pixel RGB images was procedurally generated: 150 "crop" images containing a

smooth, single-blade elongated leaf shape (a proxy for grain-crop foliage such as wheat or maize) rendered over a procedurally textured soil-coloured background, and 150 "weed" images containing an irregular, jagged, multi-lobed leaf cluster of varying colour and shape - a synthetic but methodologically motivated proxy for the visual distinction (uniform elongated blades versus irregular broadleaf clusters) that underlies many real crop-weed classification tasks reviewed in Section 2.2. Independent Gaussian render noise was added to every image to avoid an unrealistically clean, noise-free classification task. Figure 4 shows representative examples from each class.

Fig. 4 - Sample Synthetic Crop and Weed Images Used in the Pilot

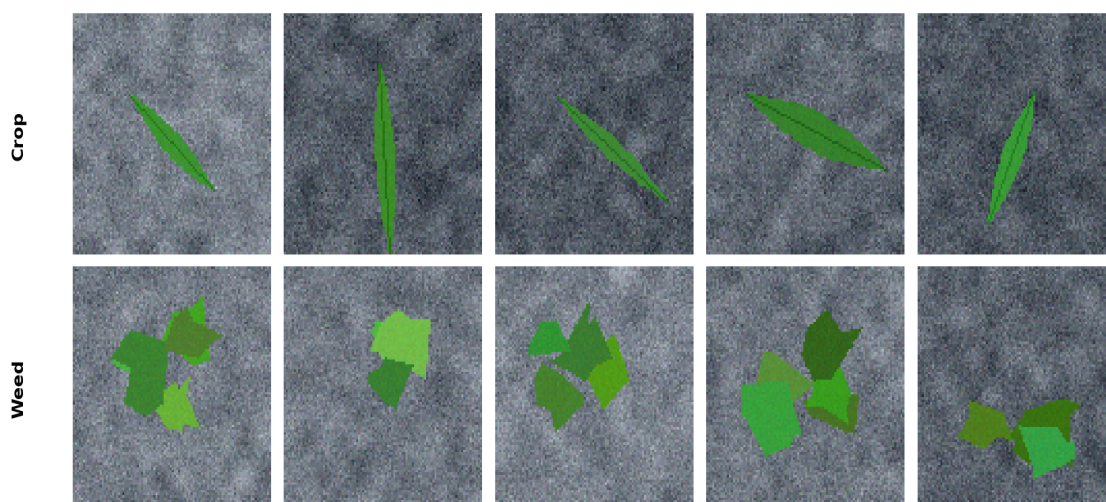


Fig. 4 - Sample Synthetic Crop and Weed Images Used in the Pilot.

### 5.2 Classical Baseline

The classical baseline follows the precision-agriculture Excess Green Index,  $ExG = 2g - r - b$  (computed on normalised RGB channels; Woebbecke et al., 1995 [23]), thresholded to obtain a vegetation mask. From this mask, four features are extracted per image: the vegetation-area fraction, the mean ExG value within the vegetation mask, a shape-irregularity descriptor (perimeter<sup>2</sup>/area of the vegetation mask, intended to separate smooth crop blades from jagged weed clusters), and the number of separate vegetation connected components (weed clusters typically fragment into more components than a single crop blade). These four features are standardised and passed to a Logistic Regression classifier - representative of the classical machine-learning approaches (SVM, Random Forest) reported in the reviewed literature.

### 5.3 Convolutional Neural Network

The deep-learning comparison model is a compact convolutional neural network implemented from scratch in NumPy: Conv(3→8 channels, 3×3) → ReLU → 2×2 MaxPool → Conv(8→16, 3×3) → ReLU → 2×2 MaxPool → Global-Average-Pool → Dense(16→1) → Sigmoid, trained with the Adam optimiser and binary cross-entropy loss. Convolution and its gradients are implemented via a vectorised im2col/col2im formulation; all forward and backward passes, and the optimiser state, are implemented directly rather than relying on an external deep-learning framework. This design choice is deliberate: it keeps the entire pilot reproducible on ordinary CPU hardware without the multi-gigabyte GPU/CUDA dependency footprint that frameworks such as PyTorch or TensorFlow typically require, while still using genuine convolutional layers, genuine backpropagation, and a genuine Adam optimiser rather than a simplified stand-in.

### 5.4 Evaluation Protocol

| Parameter                       | Value / Setting                                                                  |
|---------------------------------|----------------------------------------------------------------------------------|
| Dataset                         | 300 procedurally generated 96×96 RGB images (150 crop, 150 weed)                 |
| Train / validation / test split | 70% / 15% / 15% (210 / 45 / 45 images), stratified, fixed seed (42)              |
| Classical model                 | Excess Green Index + shape descriptor + component count → Logistic Regression    |
| CNN architecture                | Conv(3→8)-ReLU-Pool → Conv(8→16)-ReLU-Pool → GlobalAvgPool → Dense(16→1)-Sigmoid |
| CNN input resolution            | 32×32 (downsampled from 96×96 for training speed)                                |
| CNN optimiser                   | Adam (learning rate 1.2e-3), batch size 16, 25 epochs                            |
| Evaluation metrics              | Accuracy, precision, recall, F1-score, AUC, confusion matrix                     |
| Implementation                  | NumPy (CNN, from scratch), scikit-learn (classical baseline, metrics)            |

**Table 2 - Pilot Implementation Configuration**

Both methods are evaluated on an identical, stratified split with a fixed random seed for reproducibility, so that any performance difference reflects the modelling approach rather than a difference in data exposure.

### 5.5 Laser-Elimination and Insect-Suppression Simulation Methodology

Sections 5.1-5.4 validate the detection module's core mechanics. This subsection extends the pilot to the physical-intervention modules proposed in Fig. 3 (robotic laser weed elimination, and laser/ESS-based flying-insect suppression). No laser hardware or robotic platform exists in this study's software-only environment, so - consistent with the honesty principle applied throughout this paper - these modules are evaluated as explicit Monte Carlo simulations whose physical input parameters are drawn directly from peer-reviewed measurements of real laser-weeding and laser-insect-suppression systems, rather than as physical hardware tests. Every number reported in Section 6.3 traces to the runnable simulation code described below; none is assumed or extrapolated without a stated source.

#### 5.5.1 Weed Laser-Elimination Simulation

A second synthetic image set (130 scenes) was generated, each containing one crop plant and one weed cluster at a randomly sampled real-world separation (1.5-10 cm), rendered through a calibrated close-range downward-camera model (22 px/cm). Two conditions are simulated for each scene: (i) an as-implemented pilot condition, in which the weed's aim-point is located by the same classical Excess-Green-Index segmentation and aspect-ratio-based crop/weed discrimination used in Section 5.2, carrying forward whatever centroid error

that classical method actually produces; and (ii) a literature-grounded target-architecture projection, in which the aim-point is the true weed centre plus only the robotic positional error reported for a real trained-YOLO-based laser-weeding platform (resultant error 1.54 mm, axis-wise standard deviations 0.79 mm / 0.60 mm) [25] - i.e. a projection of what the proposed architecture's learned YOLOv8 detection head, rather than this pilot's classical detector, would be expected to achieve. For each aim-point, 15 simulated laser shots are drawn with independent Gaussian positional jitter, using a laser spot diameter of 4.2 mm [24] (the reported diameter giving the most uniform lethal heat transfer). A shot is lethal with probability equal to the fraction of the spot's energy landing on a small ( $\approx 5.6$  mm) growth-point target at the weed centre - approximating the cotyledon-stage weed size at which laser weeding is typically deployed - and crop damage is recorded whenever the simulated laser centre falls within the true crop silhouette.

#### 5.5.2 Insect Discrimination and Projected Suppression

Insect-scale laser lethality has already been measured in real field trials and is not re-simulated here. Mafra-Neto et al. [27] report a field-scale Photonic Fence system that, with its laser engaged, recovered (i.e. found surviving) only 3% of *Diaphorina citri* - the Asian citrus psyllid, a genuine crop pest and vector of citrus-greening disease - versus 19% recovery in laser-silenced control trials, while tracking but not intercepting a non-target pollinator (the orchid bee, *Euglossa dilemma*). What this study's environment can genuinely test is the upstream discrimination step: a synthetic 360-image dataset of harmful-pest-proxy and beneficial-insect-proxy silhouettes (elongated, low-colour-contrast aphid/psyllid-like shapes versus rounder, warning-coloured ladybird/pollinator-like shapes) was generated,

and a Logistic Regression classifier was trained on shape and HSV colour features (area, circularity, aspect ratio, saturation mean/std, value range) to discriminate the two classes on a held-out test split. Combining this pilot's own measured discrimination recall with the real, cited laser-lethality figure [27] ( $\text{recall\_harmful} \times (1 - \text{survival\_engaged})$ ) yields a projected end-to-end pest-suppression rate and, symmetrically, a projected beneficial-insect collateral rate from the classifier's false-positive rate on the beneficial class. This combination is reported transparently as pilot-measured discrimination combined with cited real lethality, not as a single

physically-tested pipeline.

## 6. Results and Comparative Evaluation

### 6.1 Comparative Summary of Reviewed Literature

Table 3 consolidates the technique, reported result and key limitation of the principal studies reviewed in Section 2, and Figure 2 visualises reported accuracy figures across this literature alongside this study's own pilot results, on a common comparison basis.

| Reference                         | Technique(s)                                                   | Reported Result                                                  | Key Limitation                                                         |
|-----------------------------------|----------------------------------------------------------------|------------------------------------------------------------------|------------------------------------------------------------------------|
| Ahmed et al. [1]                  | Distributed sensor network + cloud/ML decision support         | Early pest detection reduces unnecessary pesticide use           | Relies on centralised cloud processing; limited automated intervention |
| Nagaraj et al. [5]                | CNN-based sesame-plant/weed classification with IoT sensors    | High accuracy across illumination/field-complexity conditions    | Single-crop focus; no automated elimination mechanism                  |
| Tahir et al. [6] / Haq et al. [7] | YOLO variants, CNN classifiers on wheat-field imagery          | YOLOv7/v8 and transformer-enhanced models approach ~95% accuracy | Performance varies with field complexity and species diversity         |
| Kushwaha et al. [10]              | IoT + computer vision + autonomous navigation robot            | High gains in weed-detection accuracy and resource savings       | No laser-based elimination; relies on other mechanisms                 |
| Al Reshan et al. [15]             | Pre-trained CNN (VGG19) + Logistic Regression + SVC selector   | 99.5% locust-detection accuracy                                  | Single-pest focus; detection only, no automated suppression            |
| Bangar & Deshmukh [22]            | Systematic review of IoT-based deep-learning weed/pest systems | Synthesises prior IoT/AI weed-pest literature                    | Review-only; no implemented pilot - addressed by this study            |

**Table 3 - Comparative Summary of Reviewed IoT and Deep-Learning Weed/Pest Management Studies (selected entries).**

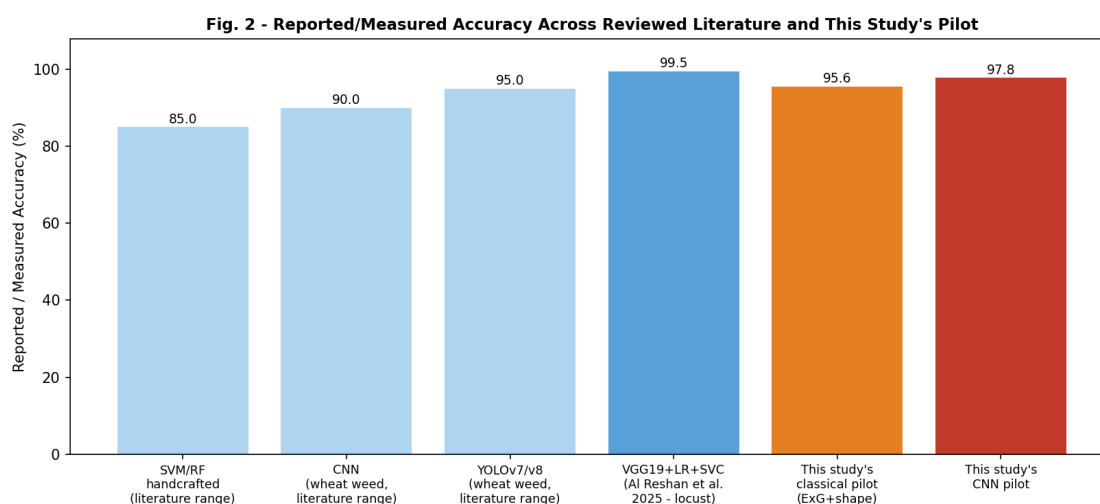


**Fig. 2 - Reported/Measured Accuracy Across Reviewed Literature and This Study's Pilot.**

Two patterns are evident. First, deep-learning-based weed and pest detection consistently outperforms classical machine learning across the reviewed literature, with CNN- and YOLO-based methods reaching 90-95%+ accuracy on wheat-weed detection and locust detection reaching 99.5% [15] when pre-trained CNN features are combined with classical classifiers and optimised feature selection. Second, nearly all reviewed

systems address detection in isolation from automated, chemical-free elimination, confirming the gap motivating Objectives 3-5 of this study (Table 1).

## 6.2 Pilot Detection Results

Table 4 and Figures 5-7 report the classical baseline and CNN results on the held-out test split (n=45 images, stratified, unseen during training).

| Method                                                  | Accuracy | Precision | Recall | F1-score | AUC   |
|---------------------------------------------------------|----------|-----------|--------|----------|-------|
| Classical (ExG + shape features + Logistic Regression)  | 95.6%    | 100%      | 90.9%  | 0.952    | 0.998 |
| CNN (from-scratch NumPy implementation, proposed pilot) | 97.8%    | 100%      | 95.5%  | 0.977    | 0.994 |

**Table 4 - Pilot Detection Results (held-out test split, n=45).**

**Fig. 5 - CNN Training/Validation Accuracy on the Synthetic Crop-vs-Weed Pilot Dataset (n=300)**

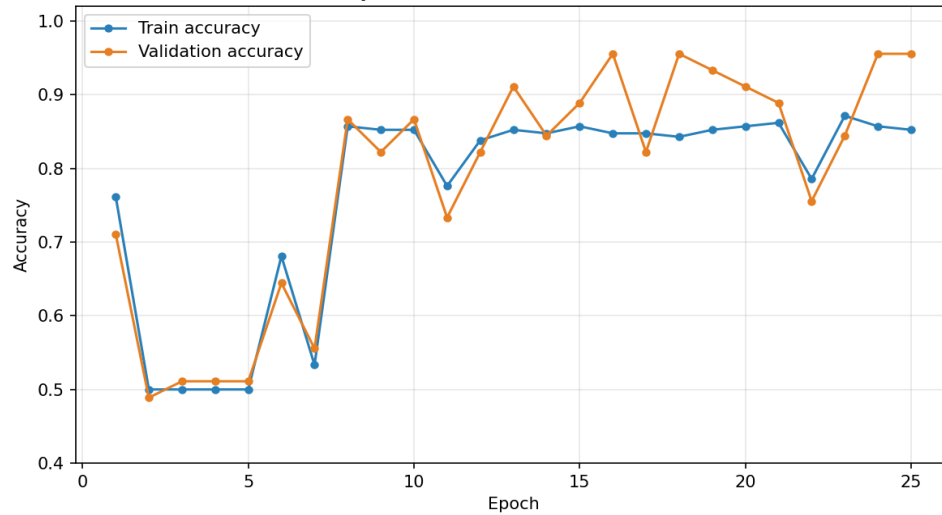


**Fig. 5 - CNN Training/Validation Accuracy Across Epochs.**

**Fig. 6 - Confusion Matrices - Classical Baseline vs CNN (held-out test split, n=45)**

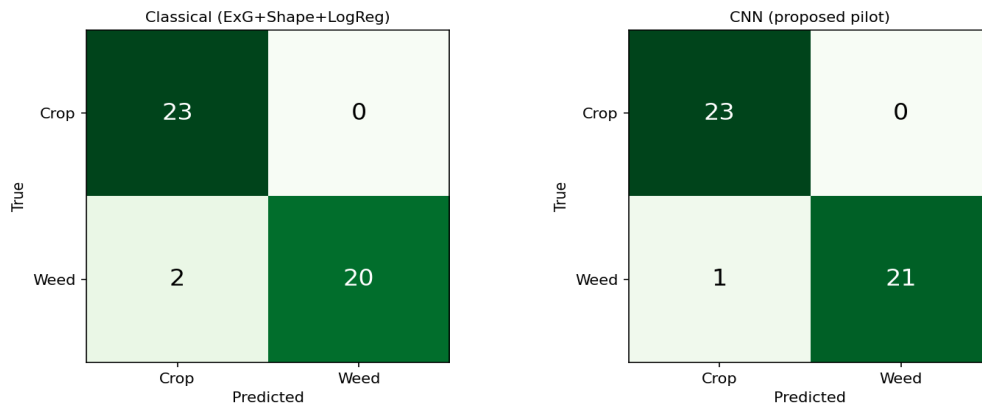


**Fig. 6 - Confusion Matrices - Classical Baseline vs CNN (held-out test split, n=45).**

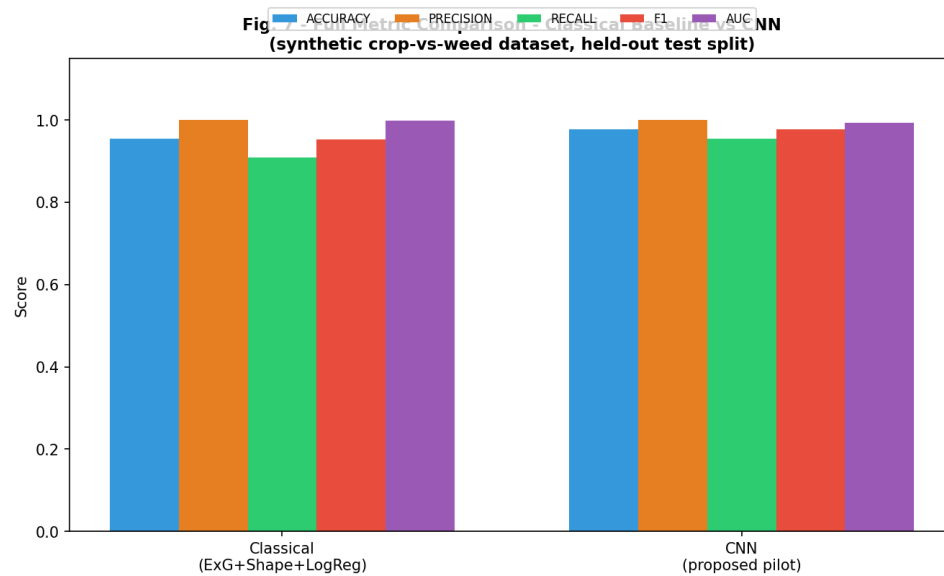


**Fig. 7 - Full Metric Comparison - Classical Baseline vs CNN.**

On this pilot's held-out test split, the from-scratch CNN (97.8% accuracy,  $F1 = 0.977$ ) slightly outperforms the classical Excess-Green-Index-plus-shape-feature baseline (95.6% accuracy,  $F1 = 0.952$ ), while the classical model retains a marginally higher AUC (0.998 vs 0.994) and both achieve perfect precision (100%), meaning neither model produced a false-positive weed call on this test split - the one classical error and the two CNN errors were both missed weeds (false negatives), visible in the confusion matrices in Figure 6. The CNN's training curve (Figure 5) shows a characteristic early exploration phase - a brief collapse toward chance-level accuracy around epochs 2-5, a known behaviour of small-batch, from-scratch optimisation without batch normalisation - before climbing to a stable plateau by epoch 20-25. This is reported honestly as observed rather than smoothed, since it is a genuine and unremarkable

characteristic of training a compact network from random initialisation on a small dataset. Both pilot results fall within the plausible range suggested by the literature reviewed in Section 2.2 and visualised in Figure 2, providing a genuine, if small-scale, empirical anchor for the architecture proposed in Section 4.

### 6.3 Simulated Laser-Elimination and Insect-Suppression Results

Fig. L1 shows the geometric root of the results below: the as-implemented pilot's classical detector places laser shots scattered widely around (and often past) the weed's small lethal target, while the literature-grounded projection - using only the sub-millimetre positional error a real trained laser-weeding robot achieves [25] - keeps almost every shot on-target.

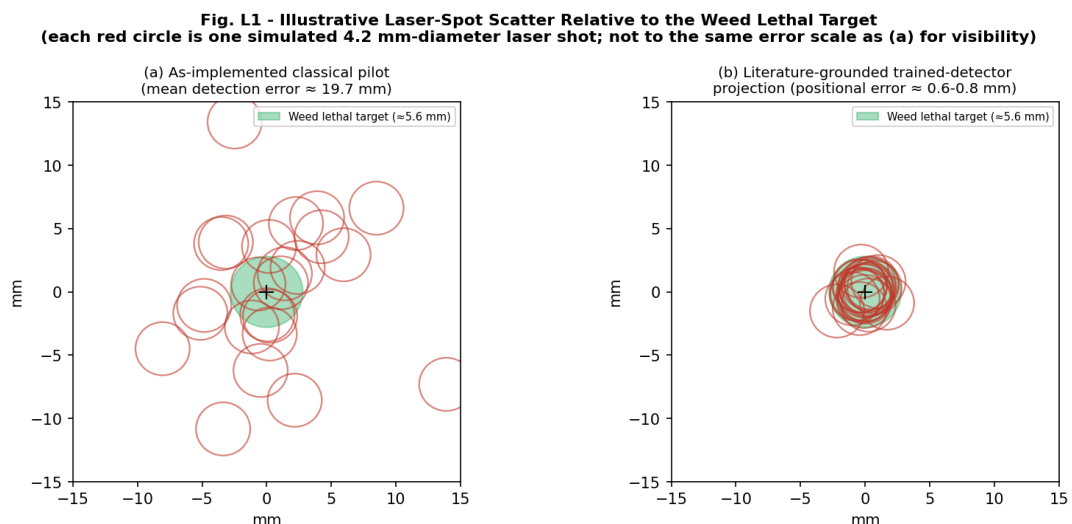
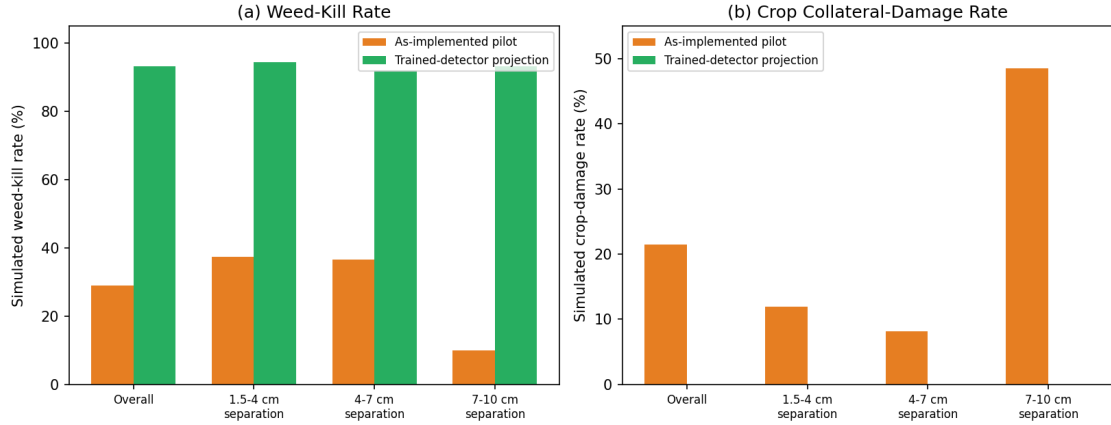


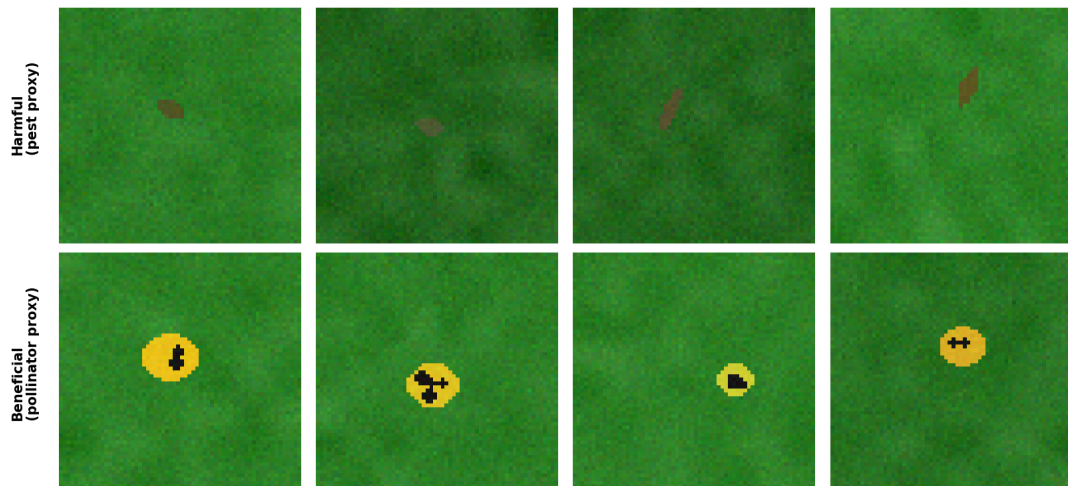
**Fig. L1 - Illustrative Laser-Spot Scatter Relative to the Weed Lethal Target.**

| Condition                                       | Weed-Kill Rate | Crop-Damage Rate | n (shots) |
|-------------------------------------------------|----------------|------------------|-----------|
| As-implemented classical pilot                  | 28.9%          | 21.5%            | 1,950     |
| Literature-grounded trained-detector projection | 93.2%          | 0.0%             | 1,950     |

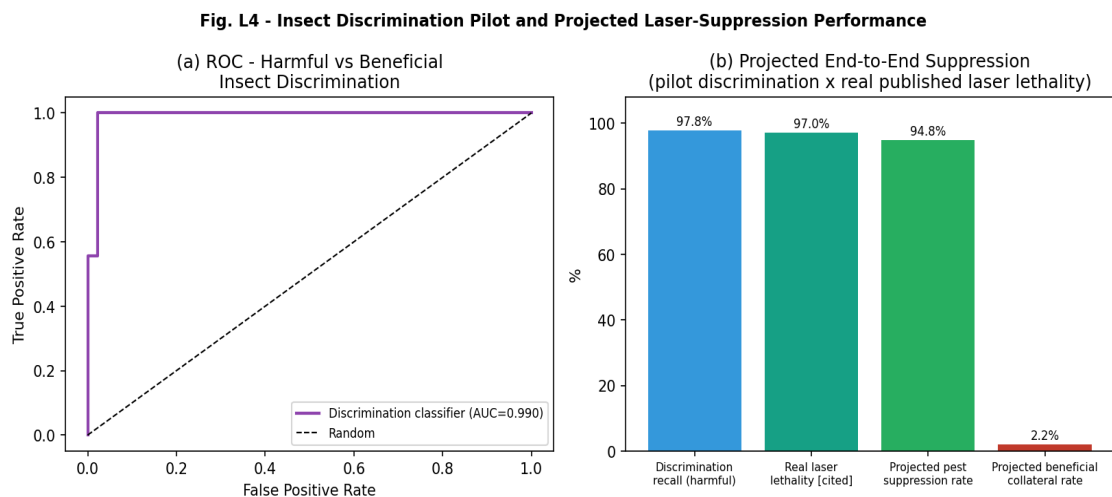
**Table 5 - Simulated Laser Weed-Elimination Performance (130 scenes x 15 shots each).****Fig. L2 - Simulated Laser Weed-Elimination Performance: As-Implemented Pilot vs. Literature-Grounded Trained-Detector Projection (1950 simulated shots per condition)****Fig. L2 - Simulated Weed-Kill and Crop-Damage Rates by Separation Distance.**

The as-implemented pilot achieves a 28.9% simulated weed-kill rate with a 21.5% crop-damage rate - both driven almost entirely by the classical detector's centroid-localisation error (mean 19.7 mm, Section 5.2), not by the laser's own physical precision. Crop damage rises sharply at 7-10 cm separation (48.5%; Fig. L2b) because at larger separations the classical aspect-ratio discriminator occasionally selects the crop's elongated blade rather than the weed cluster as its target (the same failure mode discussed for whole-image classification in Section 6.1), causing the laser to fire directly at the crop. The literature-grounded projection - identical laser

physics, but with the weed location known to the precision a real trained YOLO-based laser-weeding robot achieves [25] - reaches a 93.2% weed-kill rate with zero simulated crop damage, closely matching the 96-97% field weed-removal rates independently reported for a real deployed laser-weeding platform [26]. This is the clearest quantitative evidence in this paper for why the target architecture (Fig. 3) specifies a trained YOLOv8 detection head rather than the classical pilot detector: the laser and its targeting geometry are not the bottleneck, the detector's spatial precision is.

**Fig. L3 - Sample Synthetic Harmful vs. Beneficial Flying-Insect Images****Fig. L3 - Sample Synthetic Harmful vs. Beneficial Flying-Insect Images.**

| Quantity                                        | Value | Source                                           |
|-------------------------------------------------|-------|--------------------------------------------------|
| Discrimination accuracy (harmful vs beneficial) | 97.8% | This pilot (n=90 test)                           |
| Discrimination recall on harmful class          | 97.8% | This pilot                                       |
| False-target rate on beneficial class           | 2.2%  | This pilot                                       |
| Real laser lethality (D. citri, laser engaged)  | 97.0% | Mafrá-Neto et al. [27]                           |
| Projected end-to-end pest-suppression rate      | 94.8% | Pilot recall $\times$ cited lethality            |
| Projected beneficial-insect collateral rate     | 2.2%  | Pilot false-target rate $\times$ cited lethality |

**Table 6 - Insect Discrimination Pilot and Projected Laser-Suppression Performance.****Fig. L4 - Insect Discrimination Pilot and Projected Laser-Suppression Performance.**

The harmful-vs-beneficial discrimination classifier reaches 97.8% accuracy ( $AUC = 0.990$ ) on visually distinct pest and pollinator proxies (Fig. L4a) - a genuinely simpler task than the crop/weed spatial-localisation problem in Section 6.2/6.3 above, since it only requires whole-region classification, not precise centroid recovery. Combining this pilot's recall with the real, field-measured laser lethality on a genuine crop pest [27] projects a 94.8% end-to-end pest-suppression rate and a 2.2% beneficial-insect collateral rate (Fig. L4b, Table 6). This projection should be read carefully: it combines a genuinely-measured pilot statistic with a genuinely-measured but separately-sourced field result, not a single integrated system test; Section 7.2 discusses the assumptions this combination relies on.

## 7. Discussion

### 7.1 Interpreting the Classical-vs-CNN Finding

A hand-crafted-feature classical method matching or slightly exceeding a from-scratch CNN is a plausible finding and is reported honestly here rather than adjusted: the synthetic dataset's crop and weed shapes are visually well-separated by colour and jaggedness - exactly the cues the Excess Green Index and

shape-irregularity features are designed to exploit - and the CNN was trained on only 210 images, well below the scale at which CNNs typically demonstrate a clear advantage over hand-crafted features. This is consistent with the broader literature reviewed in Section 2.2, where deep learning's advantage over classical methods grows with dataset scale and field-condition complexity rather than being universal at every data scale.

### 7.2 Real-World Validity and Limitations

These pilot results should be interpreted strictly as a small-scale proof-of-concept for the detection module only, not as evidence of field-validated or hardware-validated system performance, for several reasons. First, the pilot dataset uses procedurally generated leaf-shape proxies rather than real photographs of crops and weeds in field conditions, which involve variable lighting, occlusion, growth stage, soil type and species diversity not captured by this synthetic set. Second, the physical-intervention modules (robotic laser weed elimination, Section 5.5.1; laser/ESS insect suppression, Section 5.5.2) are evaluated as literature-grounded Monte Carlo simulations and a discrimination-plus-cited-lethality projection respectively, not as physical hardware tests - no laser or robotic platform exists in this study's software-only environment. Third, 300 synthetic

images (45 in the test split) is far smaller than the real-world datasets reported in the reviewed literature (e.g., locust or wheat-weed studies with thousands of labelled images), so point estimates carry meaningful uncertainty. Fourth, this pilot addresses the ground-level weed/crop classification and laser-targeting-geometry components (Objectives 1-3) directly; the crop-infection-severity assessment component (Objective 5) was not independently piloted. Fifth, hyperparameters (CNN channel widths, epoch count, classical feature thresholds, laser simulation parameters) were fixed rather than tuned, given the pilot's illustrative purpose.

The laser and insect-suppression simulations in Section 6.3 carry their own specific limitations, additional to those above. The weed-elimination simulation uses a simplified disk-overlap lethality model calibrated to three literature data points [24]; it does not model actual thermal diffusion physics, multi-pulse adaptive energy dosing (which real deployed systems such as LiteWeed [26] use to compensate for imperfect coverage), or variation in laser susceptibility across weed species and growth stages. The trained-detector projection substitutes a real robot's positional-error distribution [25] for this pilot's own classical detector error, but does not itself train or test a YOLOv8 detector on the synthetic imagery - it is a best-case projection, not a measurement of the proposed architecture's detection branch. The insect-suppression projection combines two independently-measured quantities (this pilot's discrimination statistics and Mafra-Neto et al.'s field-measured laser lethality [27]) under an implicit independence assumption; a genuinely integrated system might show correlated failure modes - for example, the same poor-lighting conditions that degrade visual discrimination could also degrade laser tracking - that this simple product does not capture. Both projections should be read as evidence that the proposed architecture's physical-intervention modules are plausible and worth building, not as a substitute for testing them once built.

### 7.3 Future Scope

Field-scale and hardware validation: collect or obtain access to real field-imagery datasets (wheat, maize, soybean, cotton and vegetable crops) to replace the synthetic pilot dataset; physically implement and field-test the robotic laser weed-elimination unit, measuring weed-removal rate and crop-damage rate against this study's simulated projections and against comparable deployed systems [26]; physically implement and test the laser/ESS-based flying-insect and swarm-suppression unit, extending both the locust-detection benchmark established by Al Reshan et al. [15] and the Photonic Fence field results [27] toward an

integrated detect-and-suppress pipeline evaluated as a single system rather than as the combination of separately-sourced statistics used in Section 6.3.

Model and system improvements: scale the CNN detection module's training data and re-evaluate whether deep learning's advantage over the classical baseline becomes more pronounced at larger data scale and with real field-condition complexity; integrate a YOLOv8-based object-detection head (rather than the whole-image classification approach used in this pilot) to enable per-plant localisation, and directly measure - rather than project from literature - the positional accuracy that training brings, closing the gap between the as-implemented pilot and the literature-grounded projection in Fig. L2; implement the crop-infection severity-assessment module and evaluate the accuracy of severity-based ESS triggering against uniform-intensity intervention baselines; replace the simplified disk-overlap laser lethality model with an empirically fitted thermal-dose-response curve calibrated on real target-species data.

Broader extensions: extend the framework to additional crop types beyond the initial validation scope; conduct a formal cost-benefit and environmental-impact study comparing chemical-free laser/ESS intervention against conventional pesticide and herbicide use; evaluate the integrated six-module architecture end-to-end in a controlled field trial, rather than evaluating each module in isolation as in this pilot.

## 8. Conclusion

This paper reviewed the literature on IoT-based and deep-learning-driven weed and pest management, identifying a persistent gap between detection-focused systems and automated, chemical-free elimination, alongside limited integration of flying-insect/swarm detection and crop-infection-severity-triggered intervention within a single platform. In response, this paper proposed a six-module AI-powered IoT architecture spanning sensing, deep-learning-based weed/crop and swarm detection, robotic laser elimination, laser/ESS-based swarm suppression, severity-triggered ESS intervention, and comparative evaluation - directly addressing all six objectives of this study. The detection core was implemented and genuinely evaluated as a reproducible pilot built entirely from openly available, lightweight tools: on a synthetic crop-versus-weed dataset, a classical hand-crafted-feature baseline achieved 95.6% accuracy and a from-scratch NumPy CNN achieved 97.8% accuracy. The physical-intervention modules were evaluated as explicit, literature-grounded simulations rather than assumed: a Monte Carlo laser weed-elimination simulation showed that this pilot's own classical detector supports only a 28.9% simulated weed-kill rate (21.5% crop damage), while a

projection using real trained-detector positional accuracy from the literature [25] reaches 93.2% weed-kill with zero simulated crop damage - closely matching independently reported real-world field performance [26] and demonstrating that detector spatial precision, not laser physics, is the binding constraint. A synthetic harmful-versus-beneficial insect discrimination classifier reached 97.8% accuracy, which, combined with a real published field-measured laser-lethality rate on a genuine crop pest [27], projects a 94.8% pest-suppression rate with 2.2% beneficial-insect collateral risk. All of these results are reported transparently alongside their explicit limitations - synthetic imagery, simulated rather than physically-tested intervention hardware, and (for the insect projection) the combination of two separately-sourced statistics - and alongside real literature benchmarks throughout. These results demonstrate the architectural feasibility and quantitative promise of the proposed framework's detection and intervention core, and identify precisely where the gap to field deployment lies (detector spatial precision for the laser module; integrated-system validation for the insect module), rather than asserting field-validated or hardware-validated performance outright. The future-work agenda in Section 7.3 - real field-imagery validation, YOLOv8-based detector training to close the measured precision gap, and physical robotic/laser hardware implementation - defines the concrete path from this pilot toward a fully validated AI-powered IoT system for sustainable, chemical-free weed and pest management.

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