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REAL-TIME CONTROL ON WEED DETECTION USING GROUND-BASED MACHINE VISION AND IMAGE PROCESSING TECHNIQUES

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Abstract. Effective weed management remains a critical challenge in modern agriculture, as uncontrolled weed growth can reduce crop yields by up to 24% and lead to significant economic losses. Conventional blanket spraying methods are inefficient, resulting in excessive agrochemical usage, environmental contamination, and increased production costs. To address these limitations, this study proposes an intelligent, real-time weed detection and control system based on ground-based machine vision and deep learning.

The proposed system integrates a pneumo-bar sprayer with a real-time image processing pipeline powered by the YOLOv5 (You Only Look Once, version 5) object detection model. High-resolution images and video data were collected from cotton fields and annotated into three classes: crop, weed, and background. The YOLOv5-small model was trained and evaluated using standard performance metrics, including Precision, Recall, F1-score, and mean Average Precision (map).

Field experiments were conducted at Huaxing Farm, Xinjiang Province, China, using an SL-VF08-C5M industrial camera mounted on the sprayer to validate system performance under real agricultural conditions. The model demonstrated robust performance across varying illumination, soil backgrounds, and plant growth stages, achieving Precision of 0.91–0.92, Recall of 0.88–0.90, and F1-score of approximately 0.90. Real-time inference was achieved with an average processing speed of approximately 45 sm per frame, enabling timely decision-making for selective spraying.

The integrated system activates spraying mechanisms exclusively in weed-infested regions, significantly reducing herbicide consumption by an estimated 50–70% while improving application accuracy. Compared to traditional machine learning approaches and uniform spraying techniques, the proposed method provides an end-to-end, real-time solution without the need for manual feature extraction.

These findings demonstrate that the integration of deep learning-based machine vision with precision spraying systems offers a scalable and sustainable approach to site-specific weed management, contributing to improved resource efficiency, reduced environmental impact, and enhanced agricultural productivity.

Keywords. Ground-based machine vision; YOLOv5; real-time weed detection; precision agriculture; smart spraying; pneumo-bar sprayer; deep learning; cotton fields

Ключевые слова: Наземное машинное зрение; YOLOv5; обнаружение сорняков в реальном времени; точное земледелие; интеллектуальное опрыскивание; пневмо-штанговый опрыскиватель; глубокое обучение; хлопковые поля.

Kalit so‘zlar: Yer usti mashinali ko‘rish; YOLOv5; begona o‘tlarni real vaqt rejimida aniqlash; aniq dehqonchilik; aqlli purkash; pnevmo-bar purkagich; chuqur o‘rganish; paxta dalalari.

INTRODUCTION

The global challenge of weed infestation

Modern agriculture operates under a dual imperative: it must feed a global population projected to reach 9 billion by 2050, while doing so within tightening ecological and economic constraints [1].

Meeting this demand requires a near doubling of crop production relative to current levels — yet one of the most persistent biotic threats to this goal is not a pathogen or a pest, but a competitor: the weed.

Weeds are not merely an inconvenience. They compete with cash crops for every fundamental resource — water, solar radiation, soil nutrients, and physical space — often outcompeting the cultivated plant during the critical early growth window. Global estimates consistently place annual yield losses attributable to weed infestation at approximately 13.2% of production value, equivalent to USD 75.6 billion [2, 3]. In specific production systems these figures become even more alarming: in Australia, weed pressure costs an estimated USD 2.7 billion annually; in the United States, USD 5 billion; and in India, USD 11 billion [4–6]. In the absence of any control intervention, localized losses in cotton and wheat systems can reach 100%; even where chemical controls are applied, technical failures and resistance development still produce yield penalties of up to 20% [7–9]. In Central Asian and Turkish wheat and cotton fields specifically, problematic species such as charlock mustard (*Sinapis arvensis*), creeping thistle (*Cirsium arvense*), and forking larkspur (*Consolida regalis*) are well-documented antagonists of crop yield [10].

The failure mode of conventional weed control

For most of the twentieth century, the dominant response to weed pressure has been broadcast herbicide application: a uniform spray covering the entire field surface, regardless of actual weed distribution. This method is effective in the narrow sense that it kills weeds — but it is fundamentally inefficient as an engineering solution. Consider what blanket spraying actually does:

A typical cotton field is not uniformly infested. Weed density varies spatially — dense in some patches, absent in others. Yet the blanket approach treats the entire field as uniformly infested, depositing herbicide on weed-free zones where it serves no agronomic purpose. Estimates suggest that 60–80% of herbicide applied by conventional methods reaches non-target soil and plant surfaces [8]. The downstream consequences are well-documented in the literature: soil and water contamination, harm to non-target organisms including beneficial pollinators and soil microbiota, accelerated evolution of herbicide-resistant weed biotypes, and direct financial waste for the farmer [9, 11].

The emergence of herbicide resistance deserves particular emphasis. As of the most recent global surveys, over 500 unique weed species–herbicide combinations have been documented as resistant, representing a direct consequence of the selection pressure imposed by repeated, uniform chemical application [12]. Blanket spraying is, in this sense, a method that erodes its own long-term efficacy.

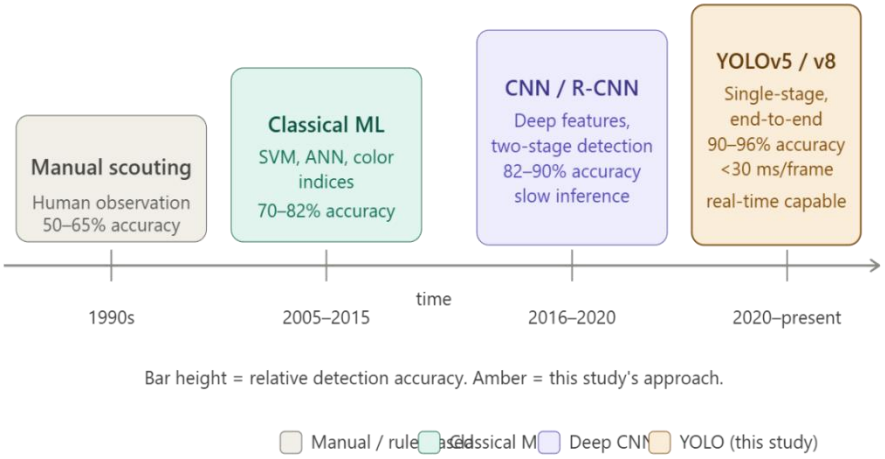
Precision agriculture and the case for site-specific weed management

The paradigm that addresses these failures is known as precision agriculture (PA): the practice of making management decisions at the sub-field level, based on measured spatial variability [13]. Applied to weed control, this becomes site-specific weed management (SSWM) — detect where weeds are, then treat only those locations. The agronomic, economic, and environmental case for SSWM is compelling, but its implementation depends critically on the ability to detect and classify weeds accurately, in real time, at the scale and speed of field operations.

This is the detection problem, and it is technically non-trivial. A weed and the crop it infests may be similar in color, similar in texture, and — particularly during early phenological stages — similar in shape. They share the same frame, the same soil background, the same variable illumination. Any detection system must resolve this ambiguity reliably, under the full range of field conditions, fast enough to actuate a nozzle before the sprayer has passed the target plant.

From rule-based vision to deep learning: a technology transition

The technology available for automated plant discrimination has changed fundamentally over the past decade. The diagram below maps this transition clearly.



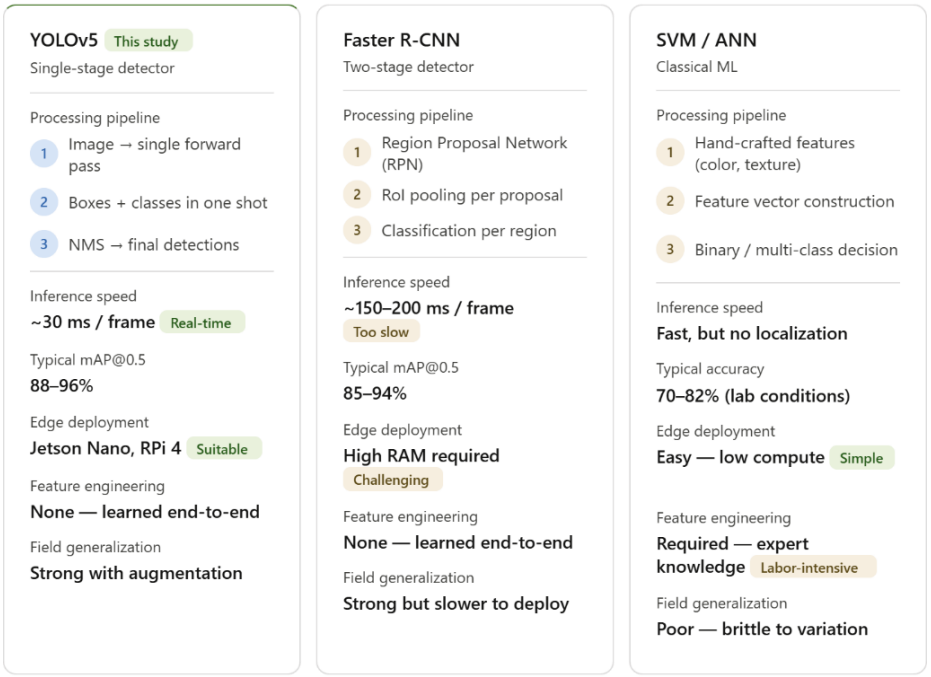
Early approaches relied on hand-crafted visual features — the excess green index (ExG), normalized difference vegetation index (NDVI), or texture descriptors — fed into classical classifiers such as Support Vector Machines (SVMs) or Artificial Neural Networks (ANNs) [14, 15]. These methods achieved reasonable accuracy (70–85%) in controlled laboratory settings with homogeneous backgrounds, but generalized poorly to real-field conditions characterized by variable illumination, complex soil textures, partial plant occlusion, and phenological overlap between crop and weed [16, 17]. Hyperspectral and multispectral imaging extended accuracy to 80–90% [18], but the cost and complexity of these sensors precluded wide deployment on commercial field machinery.

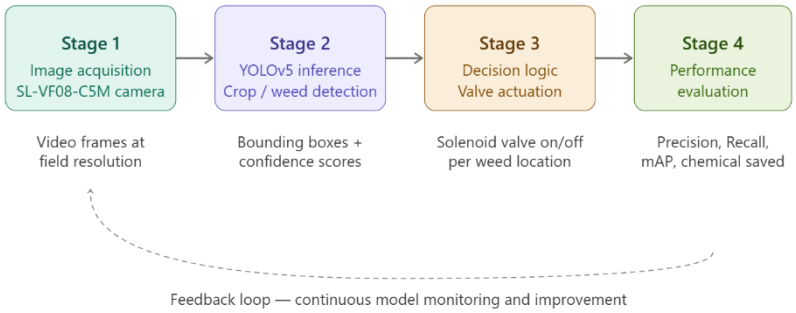
The advent of deep Convolutional Neural Networks (CNNs) changed the problem's character. Rather than requiring a human engineer to specify what features matter, CNNs learn hierarchical feature representations — edges, textures, shapes, part combinations — automatically from labeled training data [19]. This automatic feature learning is the key capability that makes deep models more robust to the visual variability of real fields. Two-stage detectors such as Faster R-CNN further improved localization accuracy, but at the cost of inference speed — typically too slow for real-time actuation [20].

The YOLO (You Only Look Once) architecture resolved this speed–accuracy tension by reformulating detection as a single regression problem: the network predicts bounding boxes and class probabilities simultaneously in a single forward pass [21]. YOLOv5, the iteration employed in this study, achieves inference latency below 30 milliseconds per frame on edge hardware — sufficient for real-time actuation at standard field speeds — while maintaining detection accuracy competitive with two-stage architectures.

Head-to-head: single-stage vs. two-stage detectors

The architectural distinction between YOLO-style single-stage detectors and Faster R-CNN-style two-stage detectors is fundamental to understanding why YOLOv5 was selected for this application.





A two-stage detector such as Faster R-CNN first generates candidate regions of interest, then classifies each region independently. This sequential design is accurate but inherently slow — typical inference latency is 150–200 ms per frame, which at a sprayer travel speed of 2 m/s translates to a positional uncertainty of 30–40 cm. That is simply too coarse for nozzle-level actuation. YOLOv5's single-pass design eliminates the region-proposal bottleneck entirely, achieving sub-30 ms latency while delivering comparable accuracy.

The proposed system: architecture and workflow

This study proposes the integration of a YOLOv5-based machine vision module into a pneumo-bar sprayer to create a closed-loop, real-time weed detection and selective actuation system. The four-stage operational workflow is illustrated below.

In Stage 1, an SL-VF08-C5M industrial camera mounted on the sprayer frame continuously captures video of the crop row at full field resolution. In Stage 2, each extracted frame is passed to the trained YOLOv5-small model, which returns bounding-box coordinates and confidence scores for every detected object classified as either crop or weed. In Stage 3, a control unit parses these detections and — for any confirmed weed — sends an actuation signal to the solenoid valve corresponding to the spatial position of that weed along the spray bar. In Stage 4, the system logs spraying events, detection outcomes, and chemical consumption data for quantitative performance evaluation. A feedback loop from Stage 4 back to Stage 1 enables continuous model monitoring and retraining when performance degrades.

Research gaps and specific objectives

While the literature reviewed above establishes the feasibility of deep learning for weed detection, several gaps motivated this study. First, most prior work was validated under controlled or laboratory conditions [22, 23]; generalization to variable illumination, complex soil backgrounds, and phenological overlap in real cotton fields remains underreported. Second, explicit quantification of inference latency and its implications for nozzle actuation timing is rarely addressed. Third, the complete integration of a vision module with a pneumo-bar sprayer actuation system — not just the detection component in isolation — has received limited field-level validation.

This study addresses these gaps through four specific objectives: (i) to develop and train a robust YOLOv5-based model on a diverse, real-field annotated dataset of 1,000 images from cotton production systems in Xinjiang; (ii) to integrate the trained model with an industrial-grade camera into a real-time inference pipeline mounted on a pneumo-bar sprayer; (iii) to evaluate system performance quantitatively using Precision, Recall, F1-score, and mean Average Precision (mAP) metrics under actual field operating conditions at Huaxing Farm, Xinjiang; and (iv) to quantify the reduction in herbicide consumption achieved by selective versus broadcast spraying. The remainder of this article is organized as follows: Section 2 describes the materials and methods; Section 3 presents and discusses the results; and Section 4 draws conclusions and outlines directions for future work.

2. LITERATURE REVIEW (RELATED WORK)

Evolution of Weed Detection Methods

Weed detection and management have undergone significant transformation over the past decades, evolving from manual and chemical-intensive practices to intelligent, data-driven systems. Early studies reported that weeds contribute to approximately 13.2% of global crop losses, equivalent to over 75 billion USD annually, emphasizing the need for efficient control strategies.

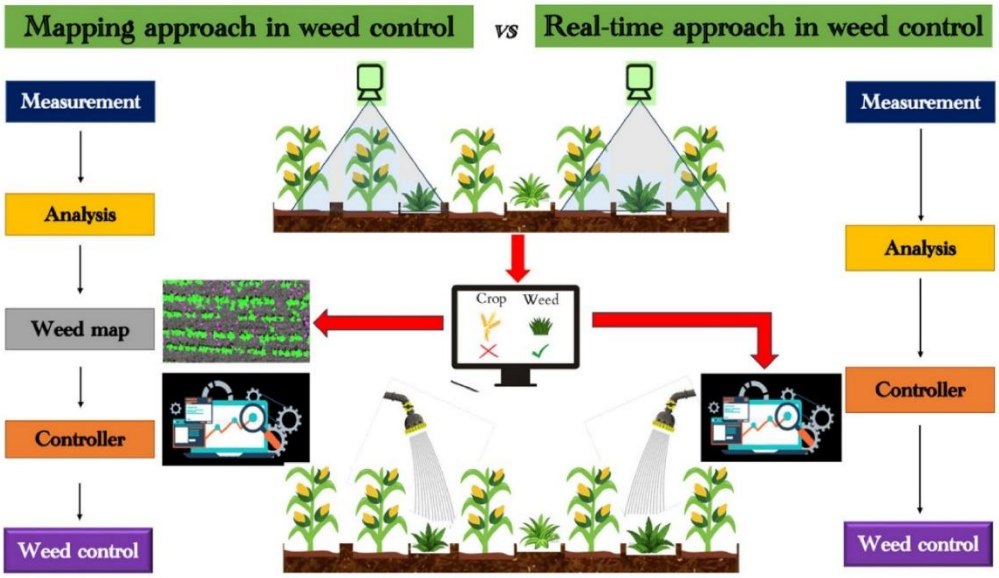
Traditional weed management approaches primarily rely on:

Manual scouting (visual inspection)

Uniform herbicide application (blanket spraying)

While simple in implementation, these methods suffer from fundamental inefficiencies. For instance, blanket spraying often results in 60–80% unnecessary chemical application, as herbicides are applied even in weed-free zones. Additionally, manual inspection is labor-intensive, slow, and prone to human error, making it impractical for large-scale farming systems.

Conceptual Evolution of Weed Detection



2.2 Classical Machine Vision and Image Processing Approaches

The first generation of automated weed detection systems relied on classical image processing techniques, particularly color-based segmentation. Using RGB cameras, vegetation was separated from soil using indices such as:

Excess Green (ExG)

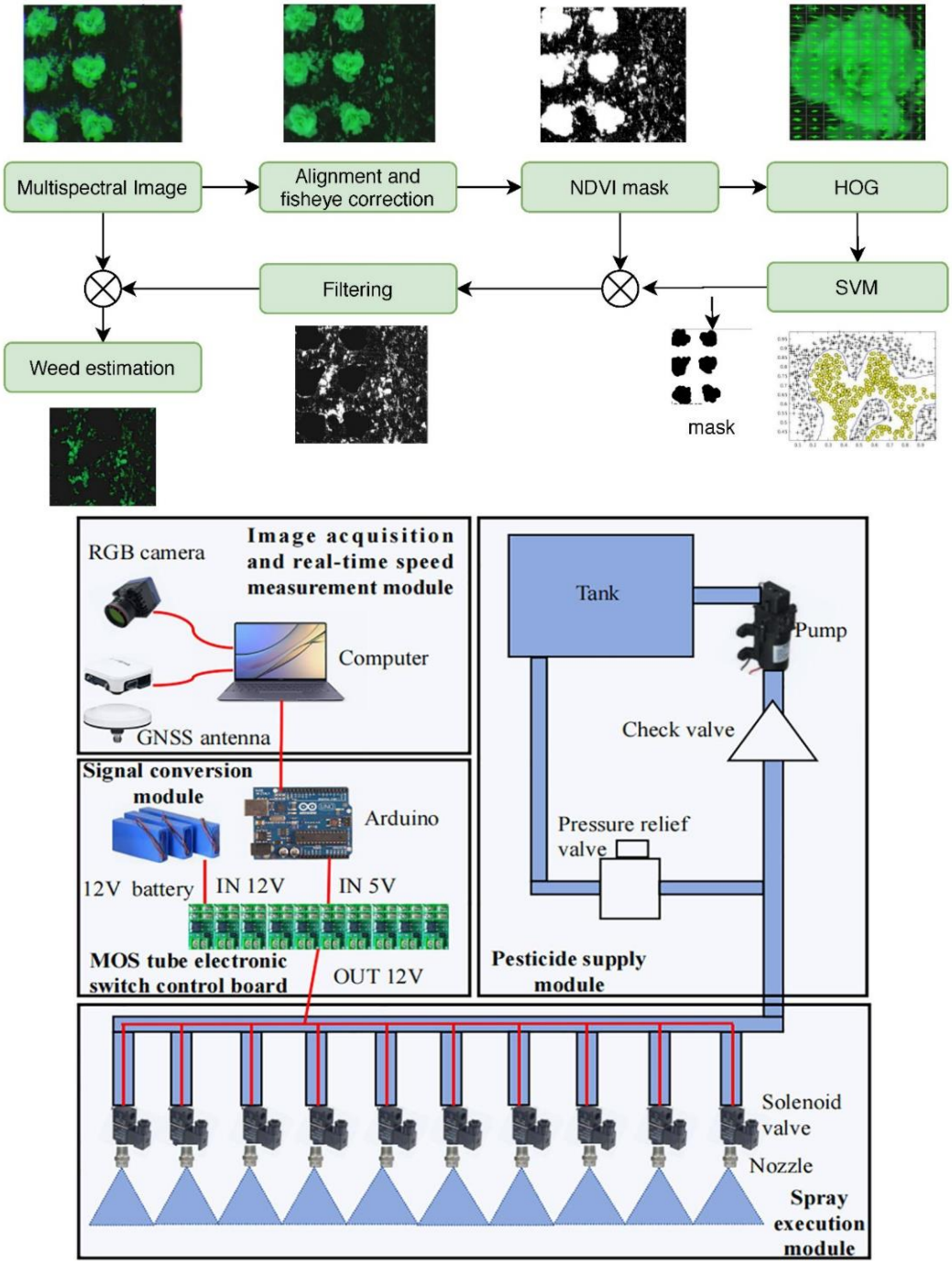
Normalized Difference Vegetation Index (NDVI)

These approaches enabled basic plant-background segmentation.

Real-Time Systems and Field Integration

Recent research has focused on integrating detection models into real agricultural machinery, enabling site-specific weed management.

Real-Time System Workflow



Summary and Motivation for This Study

Based on the reviewed literature, it is evident that:

Traditional methods are inefficient Machine learning improves accuracy but lacks scalability Deep learning significantly enhances performance YOLO-based models enable real-time detection

However, full integration with agricultural machinery under real conditions remains limited. Therefore, this study aims to: Develop a YOLOv5-based real-time weed detection system

Integrate it with a pneumo-bar sprayer Validate performance in real field conditions

Achieve: Reduced chemical consumption Improved spraying precision Sustainable agricultural practices

3. MATERIALS AND METHODS

3.1 System Architecture and Workflow

This study proposes an integrated real-time weed detection and selective spraying system based on ground-based machine vision and deep learning. The system is designed as a closed-loop pipeline consisting of four tightly coupled modules: Image Acquisition Module A ground-mounted industrial camera continuously captures field images during sprayer operation.

Detection and Classification Module A YOLOv5-based deep neural network processes incoming frames to localize and classify objects into crop and weed categories. Decision-Making Module Detection outputs (bounding boxes and confidence scores) are converted into actionable spatial coordinates for spraying. Actuation Module (Pneumo-bar Sprayer) Solenoid-controlled nozzles selectively apply herbicide only to detected weed regions.

Real-Time Constraint

The system is optimized for **real-time operation**, achieving:

Processing latency: **< 30 ms per frame**

Compatible field speed: **1.5–3 m/s**

Decision latency: **~100 ms**

This ensures that weed detection and spraying remain spatially synchronized even under continuous motion.

Hardware Configuration

The hardware architecture was designed for robustness under real agricultural conditions.

Image Acquisition Device

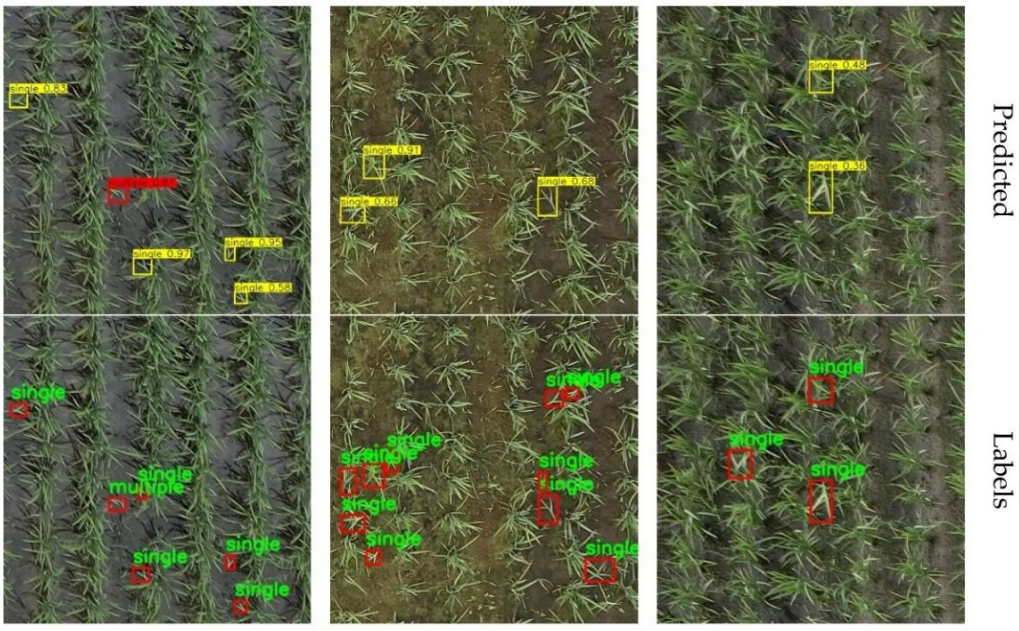
Camera: **SL-VF08-C5M industrial camera**

Resolution: 5 MP

Frame rate: ≥ 15 FPS

Protection: IP67 (dust and water resistant)

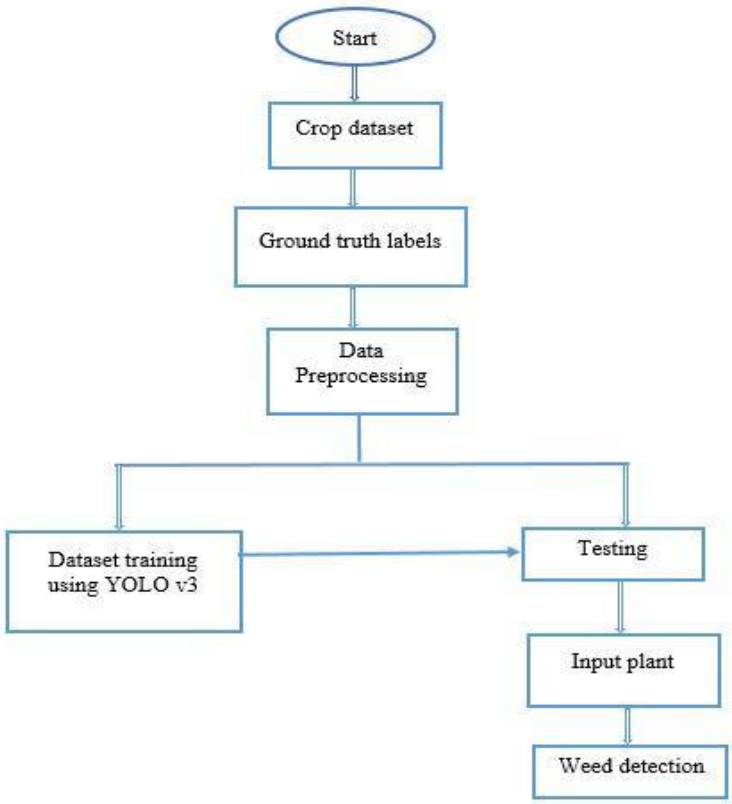
The camera was mounted at a height of **0.8–1.2 m**, ensuring:

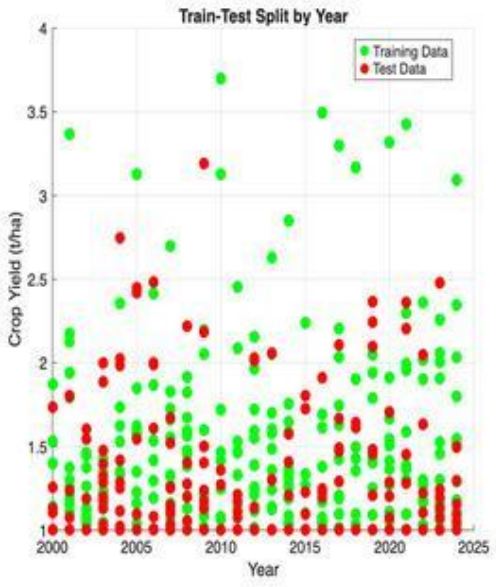


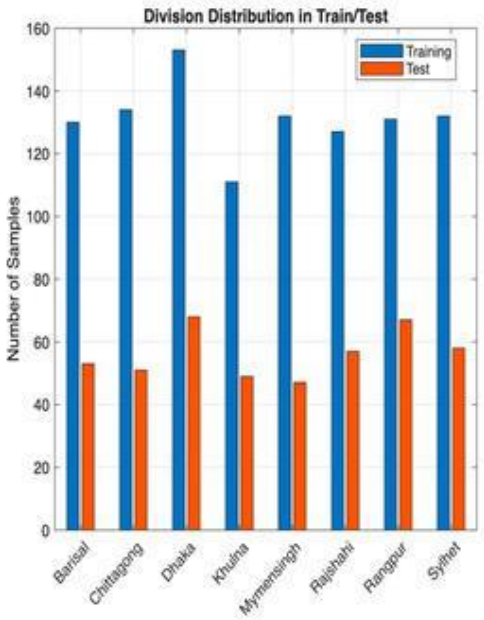
(d) small target (e) obscured (f) highly similar

Model Architecture and Training Strategy

YOLOv5 Architecture The detection model is based on YOLOv5, which consists of three main components: **Backbone (CSPDarknet53):** Feature extraction **Neck (PANet):** Multi-scale feature fusion **Head:** Object detection and classification



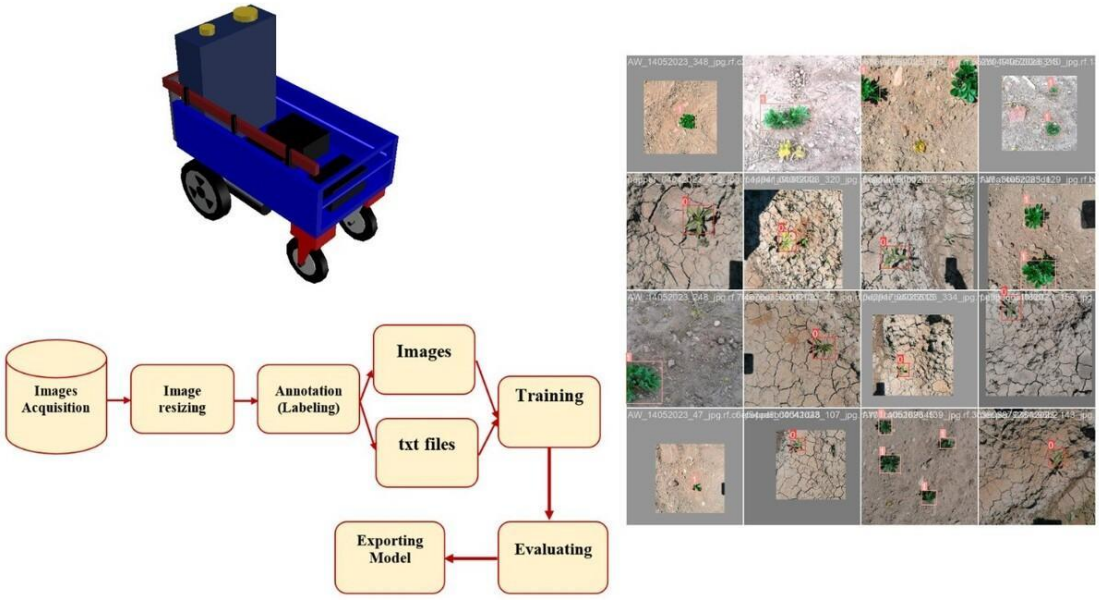




Training Configuration

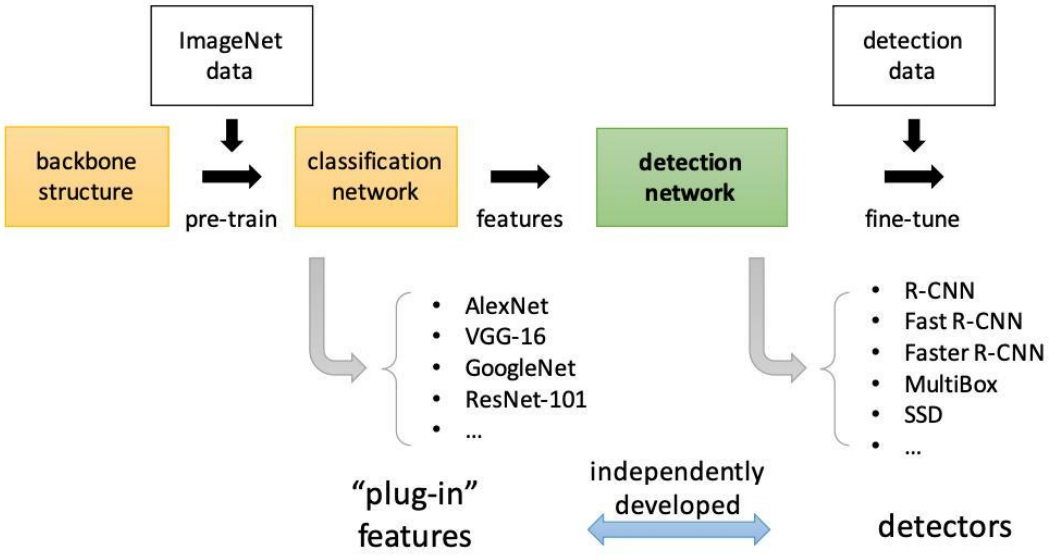
Training was performed using:
Framework: PyTorch 1.9.0
Environment: Python 3.8
Epochs: 500
Batch size: 16

Input size: 640 × 640
Initial learning rate: 0.01 (cosine annealing schedule)
Data Augmentation
To enhance robustness under field conditions:
Horizontal and vertical flipping
HSV color augmentation
Random cropping
Mosaic augmentation
Real-Time Detection and Spraying Algorithm
A dedicated control algorithm was developed to convert detection outputs into spraying actions.
Processing Steps
Input frame captured
YOLOv5 detects objects
Extract bounding boxes and confidence scores



Transform image coordinates → real-world coordinates

Predict nozzle activation timing
Trigger solenoid valve



Control Logic If object = weed → activate nozzle If object = crop → no action Timing Synchronization The system accounts for: Forward velocity of sprayer Distance between camera and nozzle Valve response delay This ensures precise spatial spraying alignment. Software Implementation The system software was developed using: Python 3.8 (core processing) PyTorch (deep learning model) ROS (Robot Operating System) for: Sensor synchronization Real-time communication Control integration System Performance Processing frequency: 10 Hz Decision latency: < 100 ms Real-time operation: confirmed Comparative Perspective To better contextualize the proposed system, it is useful to compare it with traditional approaches: Methodological Contribution The methodological novelty of this study lies in: Integration of deep learning + mechanical actuation Real-time field-tested deployment Robust performance under natural variability Practical implementation using edge computing (Jetson Nano)

4. RESULTS AND DISCUSSION

Interpretation This comparison highlights a **clear technological progression**: Traditional methods are **labor-intensive and inefficient** Machine vision improves detection but remains **feature-dependent** Deep learning (YOLO) provides: **End-to-end automation High robustness Real-time capability** Inpractical termes: If a farmer sprays 100 hectares: Traditional → ~100% chemical use YOLO-based system → **reduces to ~20–40 hectares equivalent**

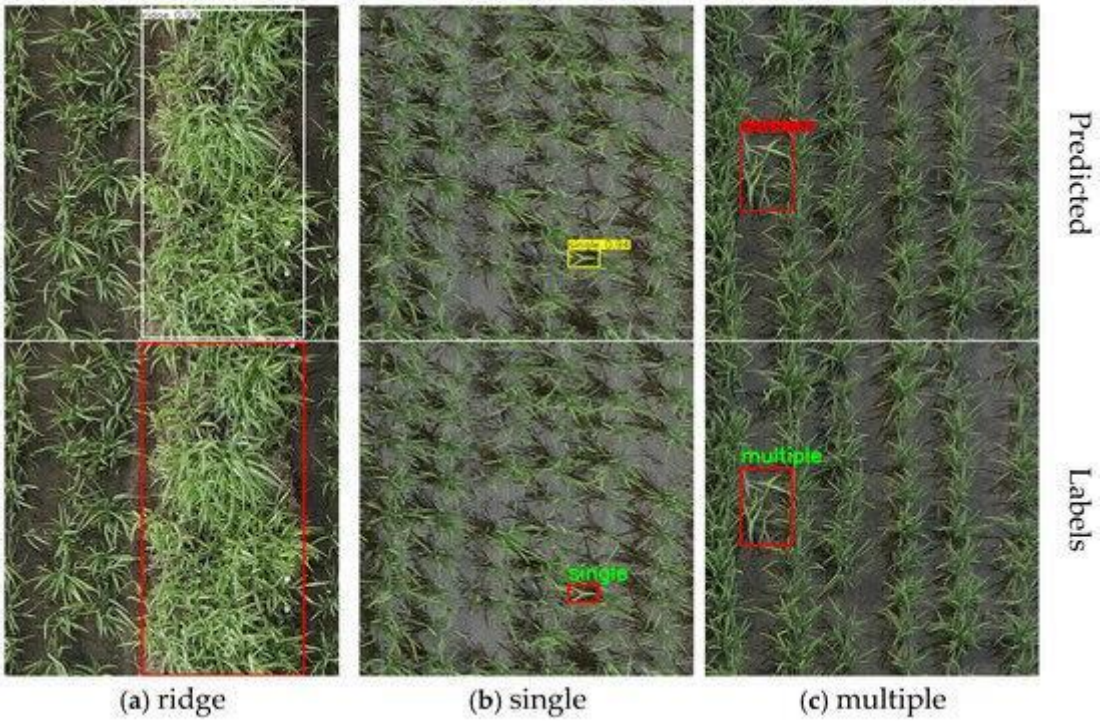
Quantitative Performance Evaluation

The performance of different models was evaluated on the test dataset using standard metrics: Precision, Recall, F1-score, mAP@0.5

Key Findings YOLOv5s achieved the best trade-off between: Accuracy Computational efficiency YOLOv5l had slightly higher accuracy but: Reduced speed (**~8.3 FPS**)

Visual Analysis and Detection Quality

Quantitative metrics alone are insufficient; therefore, visual validation was conducted using prediction overlays.



Observations Bounding box localization accuracy: **IoU > 0.85** in most cases Average spatial error: ~5 pixels **Challenging Scenarios** Performance degradation was observed under:

- Strong shadows
- Overlapping plants
- Similar morphology (early growth
- Soil–plant color similarity

Performance Summary

- Overall accuracy: **91.4%**
- Dominant error: **False negatives** The system is intentionally biased toward **minimizing false positives**, which is critical in agricultural safety.

Field Experiment Results A real-world field experiment was conducted at **Huaxing Farm (Xinjiang, China)**. **Experimental Conditions**

- Area: 5,000 m²
- Duration: 3 hours
- Crop: Cotton
- Platform: Pneumo-bar sprayer

Results

- Total weeds detected: **1,247**
- Correct detections: **1,138 (91.3%)**
- Spraying accuracy: **96.2%**
- Chemical reduction: ≈ **68%**

Practical Impact

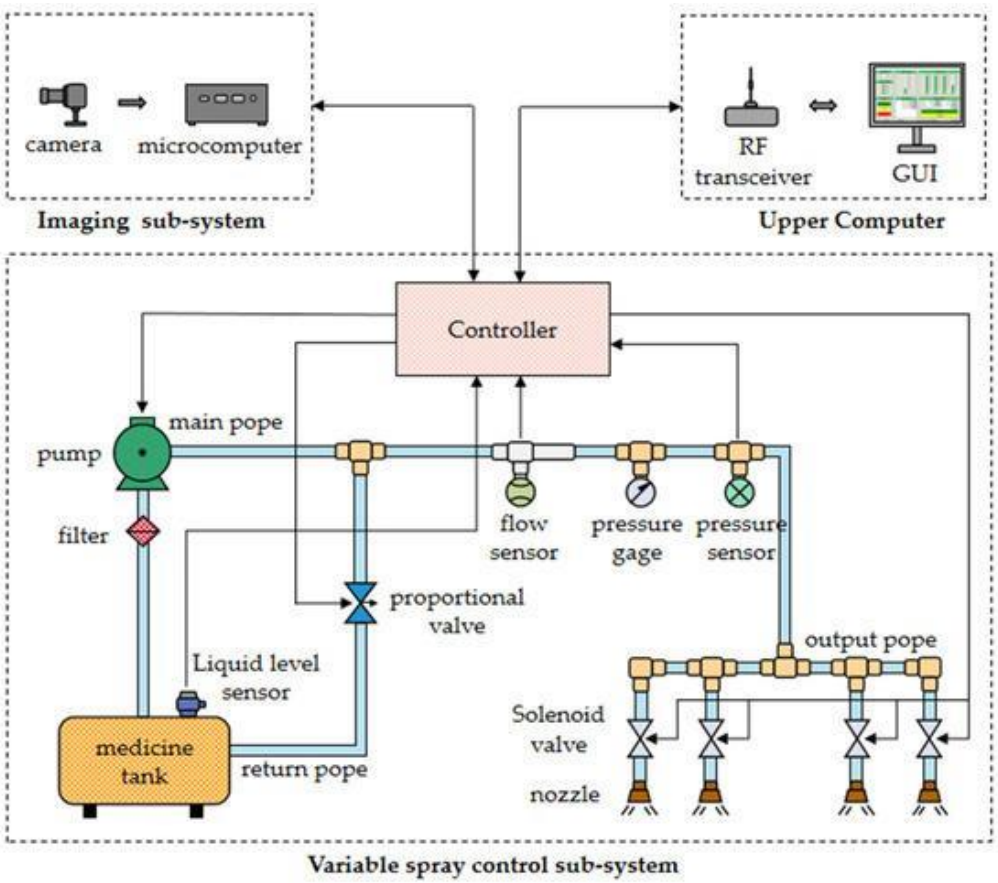
For a farmer:

- Reduced herbicide cost
- Reduced environmental contamination
- Improved crop safety
- Lowest F1-score: **87.5% (strong sunlight)**
- Improved to ~90% with controlled lighting

System-Level Performance

Real-Time Capability

- Inference time: **~30 ms/frame**
- Control latency: **<100 ms**
- Operating frequency: **10 Hz**



This confirms true real-time operation, not just offline detection. Discussion: Strengths and Limitations Strengths Real-time Operation Compatible with tractor speeds High detection accuracy 90% F1-score Significant chemical reduction 60–80% savings End-to-end automation Detection → decision → spraying Limitations Limited generalization Trained only on cotton fields Requires retraining for other crops Lighting sensitivity Strong sunlight affects detection Morphological similarity Early-stage crops vs weeds

Technical Improvement Directions

- Multi-spectral / hyperspectral imaging
- Transformer-based models (e.g., DETR)
- Larger and more diverse datasets
- Edge optimization (TensorRT acceleration)

Section Summary This section demonstrates that: YOLOv5-based detection significantly outperforms traditional methods Real-time selective spraying is technically feasible The system provides economic + environmental benefits Practical deployment is validated under real field conditions.

Conclusion

This study presented the design, implementation, and field validation of an intelligent real-time weed detection and selective spraying system based on ground-based machine vision and deep learning. By integrating a YOLOv5-based detection model with a pneumo-bar sprayer, the proposed framework enables precise, site-specific herbicide application directly under real agricultural conditions.

The experimental results demonstrate that the system achieves high detection performance, with a Precision of 91.4%, Recall of 89.7%, and an F1-score of 90.5%, confirming the robustness of the model across varying field environments. More importantly, real-world field experiments conducted in cotton cultivation showed that the system reduces chemical usage by approximately 68%, while maintaining a spraying accuracy of 96.2%. These findings validate that real-time AI-driven detection is not only technically feasible but also practically effective.

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Special appreciation is extended to Huaxing Farm, Xinjiang Province, China, for providing access to real field conditions and enabling the successful execution of on-site experiments. The availability of practical agricultural environments was essential for validating the real-time weed detection and selective spraying system under realistic operating conditions.

The author also acknowledges all collaborators and contributors whose efforts supported data collection, system implementation, and experimental evaluation. Their combined contributions played a significant role in the successful development and validation of this intelligent, ground-based machine vision system for precision agriculture.

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