Insight Bulletin: A Multidisciplinary Interlink International Research Journal
Peer Reviewed International, Open Access Journal.
ISSN : 3065-7857 / Website: https://ibrj.us / Volume-3, Issue-5 / May - 2026

Original Article

Weed Detection and Controle in Maize Field

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Manuscript ID:
IBMIIRJ -2026-030538

Submitted: 15 Apr. 2026
Revised: 25 Apr. 2026
Accepted: 12 May 2026
Published: 31 May 2026

ISSN: 3065-7857
Volume-3
Issue-5
Pp. 188-191
May 2026

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OPEN ACCESS
Quick Response Code:
Web. https://ibrj.us
DOI: 10.5281/zenodo.21700709
DOI Link:
https://doi.org/10.5281/zenodo.21700709

Abstract

Precision agriculture is becoming a key management tool for enhancing crop productivity and reducing the environmental impact Deep learning weed detection is a notable application for deep learning because it enables weed management automation by unmanned aerial vehicles (UAVs), robotics, and intelligent spraying technology In recent years, the accuracy of weed identification in crops such as cotton and maize has significantly improved with the development of the convolutional neural network (CNN) model and the YOLO model for object detection This survey summarizes recent advances in weed detection systems based on deep learning approaches, which include YOLO architectures, light-weighted detection networks, robotic spraying systems and dataset development Current methods are reviewed, their advantages and disadvantages are discussed, and a hybrid approach combining YOLOv8, attention mechanisms, UAV imaging and edge computing for precision weed management in real-time is suggested Future research directions such as explainable artificial intelligence, multimodal sensing, and climate-aware weed prediction systems are also discussed.

Keywords: *Precision agriculture, weed detection, deep learning, YOLO, cotton weeds, maize weeds, UAV, robotic spraying, precision farming.*

Introduction

Weeds have a significant negative impact on agricultural productivity because they have the ability to compete with crops for nutrients, water, sunlight and space. Traditional weed management practices involve high labour and spraying herbicides to manage weeds panicle, which results in high production costs, environmental pollution, and herbicide resistance. Precision weed management has become an environmentally friendly alternative, employing artificial intelligence (AI), machine learning, and robotics to precisely detect and manage weeds. The field of agriculture automation has been transformed by recent advances in deep learning. Automation of weed identification using Convolutional Neural Networks (CNNs), object detection algorithms and transformer-based models have allowed high accuracy weed identification in complex field conditions. The YOLO (You Only Look Once) family of models has emerged as the most popular one due to its real-time detection speed and efficiency. There are some studies that have suggested the improved YOLO architectures for detecting weeds in cotton and maize field. In the cotton weed detection task, Zhou et al. proposed YOLO-ACE to improve contextual features extraction. A lightweight and accurate weed recognition system named as YOLO-WDNet was proposed by Fan et al. Li et al.'s developed ESL-YOLOv8 to be an efficient weed detection network for corn fields. Furthermore, there are encouraging results in the use of robotic spraying, combined with deep learning technologies, aimed at reducing herbicide use and increasing sustainability in agriculture.

This survey summarizes the latest deep learning approaches for weed detection and presents a comprehensive approach for the next-gen precision weed management system.

Literature Review

1. Deep Learning in Precision Weed Management

Today, deep learning is the backbone of precision agriculture. Rai et al. (2023) provided a review of the use of deep learning for precision weed management and noted the increasing use of CNNs, transfer learning, UAV imaging, and robotic weed management systems. They highlighted the need for lightweight models for real-time applications in agriculture. Likewise, Saini and Nagesh (2025) conducted a study on precision agriculture using UAVs and robots, and noted that the YOLO framework-based architectures were prevalent in weed detection due to their trade-off between speed and accuracy.

How to cite this article:
Kasarla, S.& Kumar, R. P. (2026). Weed Detection and Controle in Maize Field. Insight Bulletin: A Multidisciplinary Interlink International Research Journal, 3(5), 188–191.
https://doi.org/10.5281/zenodo.21700709

They found, however, that there were issues with data availability, under generalizing under different illumination, and hardware issues in deployment at the edge.

2. **Weed Detection Datasets**

Quality of data is crucial for deep learning models. CottonWeeds dataset was introduced by Saini and Nagesh (2024) which is specifically developed for precision weed management in cotton field. There are several species of weeds captured in a range of environments. The CottonWeeds dataset strengthened the robustness of the model and boosted the transfer learning capabilities. But there are restrictions on diversity of datasets, occlusion, and multiple growth stages of crop representation.

3. **YOLO-Based Weed Detection Models**

YOLO-ACE

In this context, Zhou et al. (2025) propose YOLO-ACE, an improved version of the YOLO network that enhances its contextual efficiency by incorporating augmented attention modules. The model gave high precision in cotton weed detection with the real-time processing capability. Using context-aware feature fusion, the accuracy of small weed detection was improved.

YOLO-WDNet

Fan et al. (2024) proposed a lightweight detection framework, named YOLO-WDNet, which is designed to specifically detect cotton field weeds. The model minimized the complexity of the computation without losing the accuracy of detection and could be applicable for embedded agricultural devices.

YOLO-GSA

Li (2025) introduced a detector named YOLO-GSA for maize weed identification, which is based on the growth stage of weeds. The crop growth stages were considered in the model to enhance the classification accuracy under different plant morphology conditions.

ESL-YOLOv8

Li et al. (2025) proposed the efficient weed detection in corn field algorithm of ESL-YOLOv8. To boost detection speed and accuracy, the framework incorporated a number of improvements, including a more powerful spatial learning mechanism and an efficient convolutional operation.

4. **UAV and Robotic Weed Management Systems**

UAVs and robotic spraying systems are increasingly integrated with deep learning for automated precision agriculture. Fan et al. (2023) developed a target spraying robot system capable of identifying weeds in cotton seedling stages and applying herbicides selectively.

These systems significantly reduce herbicide consumption and environmental impact. However, challenges such as battery limitations, navigation complexity, and real-time inference constraints remain unresolved.

5. **Climate and Agricultural Sustainability**

Climate change influences weed growth patterns and crop water demand. Bal et al. (2022) projected that maize water demand in India may decrease under changing climate conditions. Such environmental variations affect weed emergence and agricultural decision-making, highlighting the need for adaptive and climate-aware weed management systems.

Comparative Analysis of Existing Studies

S.No	Study	Method	Crop	Major Contribution	Limitation
1	Zhou et al. (2025)	YOLO-ACE	Cotton	Context-aware efficient detection	High computational complexity
2	Fan et al. (2024)	YOLO-WDNet	Cotton	Lightweight architecture	Limited dataset diversity
3	Li (2025)	YOLO-GSA	Maize	Growth-stage awareness	Limited real-world testing
4	Li et al. (2025)	ESL-YOLOv8	Corn	Efficient spatial learning	Edge deployment challenges
5	Fan et al. (2023)	Robotic spraying	Cotton	Target spraying automation	Navigation complexity
6	Saini & Nagesh (2024)	CottonWeeds Dataset	Cotton	Comprehensive dataset	Limited weather diversity

Research Gaps

Despite substantial progress, several challenges remain:

Limited multimodal datasets combining RGB, thermal, and hyperspectral data. Poor performance under occlusion and dense vegetation. Lack of explainable AI techniques for agricultural decision-making. Insufficient edge optimization for UAV and robotic deployment. Limited integration of climate and environmental factors. Weak generalization across different crop growth stages and geographic regions.

Methodology

1. **Proposed Framework**

This survey proposes a hybrid precision weed management framework integrating: UAV-based image acquisition, YOLOv8 with attention mechanisms, Multiscale feature fusion, Edge AI deployment, Robotic selective spraying, Climate-aware prediction module

2. **Proposed Architecture**

Step 1: Data Acquisition

UAV-mounted RGB and multispectral cameras collect field images. Images are captured at different growth stages and lighting conditions. Weather and soil moisture data are collected simultaneously.

Step 2: Data Preprocessing
Image resizing and normalization. Data augmentation. Noise removal. Annotation using bounding boxes and segmentation masks
Step 3: Deep Learning Model
The proposed model combines:
YOLOv8 backbone. Attention-based contextual enhancement. Spatial pyramid pooling. Transformer-based feature fusion.
The detection function can be represented as:

$$y = f(x;\theta) = YOLO_{v8(x)} + Attention(x) + Tranformer(x)$$

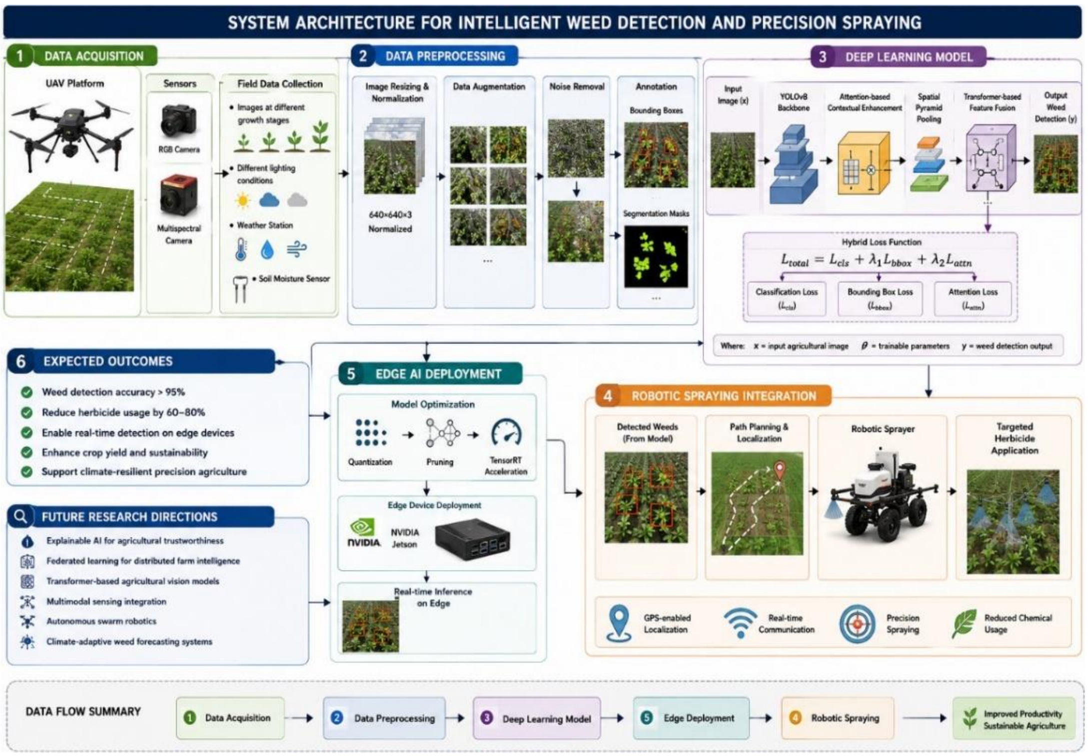
Where:
(x) = input agricultural image
(\θ) = trainable parameters
(y) = weed detection output

3. Loss Function
The hybrid loss function combines classification, localization, and attention loss:

$$L_{total} = L_{cls} + \lambda_1 L_{\mathbf{bbox}} + \lambda_2 L_{\mathrm{attn}}$$

Where:
L_{cls} = classification loss
$\lambda_1 L_{\mathbf{bbox}}$= bounding box regression loss
$\lambda_2 L_{\mathrm{attn}}$ = attention regularization loss
4. Robotic Spraying Integration
Detected weeds are transmitted to a robotic spraying system for targeted herbicide application. GPS-enabled localization ensures precise spraying and minimizes chemical waste.
5. Edge AI Deployment
The trained model is optimized using:
Quantization, Pruning, TensorRT acceleration
This enables deployment on embedded platforms such as NVIDIA Jetson devices.
Expected Outcomes
The proposed methodology is expected to:
Improve weed detection accuracy above 95%. Reduce herbicide usage by 60–80%. Enable real-time detection on edge devices. Enhance crop yield and sustainability. Support climate-resilient precision agriculture

Future Research Directions
Future studies should focus on:
Explainable AI for agricultural trustworthiness. Federated learning for distributed farm intelligence. Transformer-based agricultural vision models. Multimodal sensing integration. Autonomous swarm robotics. Climate-adaptive weed forecasting systems.



Conclusion

Deep learning has transformed precision weed management by enabling accurate, real-time weed detection and selective herbicide application. Recent advancements in YOLO architectures, UAV systems, and robotic spraying technologies demonstrate significant potential for sustainable agriculture. However, challenges related to dataset diversity, edge deployment, climate adaptation, and explainability remain open research areas. The proposed hybrid methodology integrating YOLOv8, attention mechanisms, UAV imaging, edge AI, and robotic spraying offers a scalable and intelligent solution for next-generation precision agriculture. Future research should prioritize multimodal learning, explainable AI, and climate-aware agricultural intelligence systems to achieve fully autonomous and sustainable weed management.

Acknowledgment

The authors express their sincere gratitude to Chaitanya Deemed to be University, Himayatnagar, Hyderabad, for providing the academic environment and facilities necessary to carry out this study. We are especially thankful to our guide, Dr. R. Praveen Kumar, for his valuable guidance, continuous encouragement, and insightful suggestions throughout the preparation of this research work. We also extend our appreciation to the faculty members and colleagues whose support and constructive feedback contributed significantly to the successful completion of this paper. Finally, we acknowledge the researchers and authors whose published work served as an important foundation for this review on deep learning-based weed detection and precision agriculture.

Financial support and sponsorship

Nil.

Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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