Deep Learning in Precision Weed Management

Dameruppula Pranaswi*[1], Rajeshwar Malavath[2], M. Parimala Kumar[3], U. Nagabhushanam[4], Bonagiri Soumya[1] and Jhansi Katike[1]

[1] *Ph. D. Scholar, Department of Agronomy, College of Agriculture, Rajendranagar, PJTAU, Hyderabad.*
[2]*Professor, Department of Soil Science and Agricultural Chemistry, College of Agriculture, Rajendranagar, PJTAU, Hyderabad.*
[3]*Scientist, Department of Agronomy, Rice Research Unit, ARI, Rajendranagar, Hyderabad.*
[4]*Professor, Department of Agronomy, Agricultural College, PJTAU, Warangal.*

Corresponding Author
Dameruppula Pranaswi
Email: dpranaswi@gmail.com

OPEN ACCESS

Keywords

Deep learning, Robots, Site specific weed management, UAV

How to cite this article:

Pranaswi, D., Malavath, R., Kumar, M. P., Nagabhushanam, U., Soumya, B. and Katike, J. 2026. Deep Learning in Precision Weed Management. *Vigyan Varta* 7 (04): 136-140.

ABSTRACT

Deep learning (DL) is transforming weed management by enabling precise, automated detection and classification, crucial for site-specific weed management (SSWM). This approach minimizes herbicide use and environmental impact, addressing the substantial global economic losses (USD 75.6 billion annually) caused by weeds. DL models, often integrated with UAVs and ground robots, utilize architectures like YOLO and Mask R-CNN for accurate weed identification and targeted intervention. While beneficial, challenges include data scarcity, the "green-on-green" problem, and real-time performance on edge devices. Future directions involve adaptive frameworks, cross-domain transfer learning, and hybrid DL architectures to enhance robustness and generalization.

INTRODUCTION

Deep learning has emerged as a transformative technology in agricultural practices, particularly for efficient weed management, addressing the critical challenge weeds pose to global food security (Rahman *et al*., 2025, *Murad et al*., 2023). Weeds compete aggressively with crops for essential resources such as light, water, nutrients, and space, leading to significant yield reductions and increased farming costs (Keerthi *et al.,* 2025). Globally, economic losses due to weed infestations are estimated to be substantial, reaching approximately USD 75.6 billion annually. Traditional weed control methods, often involving blanket herbicide spraying, contribute to environmental contamination, soil damage, and the development of herbicideresistant weed populations, posing risks to human health and agricultural sustainability (Sandoval-Pillajo *et al*., 2025). Precision agriculture leveraging advancements in artificial intelligence (AI) and deep learning (DL), offers a more sustainable solution by enabling sitespecific weed management (SSWM) (Vasileiou *et al*., 20240.

Deep learning, a key subfield of AI, facilitates automated detection, localization, and classification of weeds with high accuracy. This capability is crucial for developing smart spraying systems and robotic weed removal technologies that minimize herbicide usage by targeting only the undesirable plants. The ability of DL models to learn complex features directly from raw image data, rather than relying on handcrafted features, provides a significant advantage over traditional machine vision techniques, enhancing robustness and recognition accuracy (Zhao *et al*., 2026).

The role of deep learning in precision weed management

The application of deep learning in weed management typically involves several stages, often forming a continuous feedback loop: image acquisition, preprocessing, model architecture design, detection/classification, and actuation

1. **Image acquisition:** High-resolution images are vital for effective weed detection. Unmanned Aerial Vehicles (UAVs), also known as drones, equipped with various imaging sensors (e.g., RGB, multispectral) are increasingly utilized for collecting agricultural field data. UAVs offer advantages in capturing large areas quickly and providing a top-down view, which helps in differentiating weeds from crops. Groundbased vehicles, including agricultural robots, also play a role in collecting close-up images, particularly for detailed plant-level analysis (Gao *et al*., 2024).

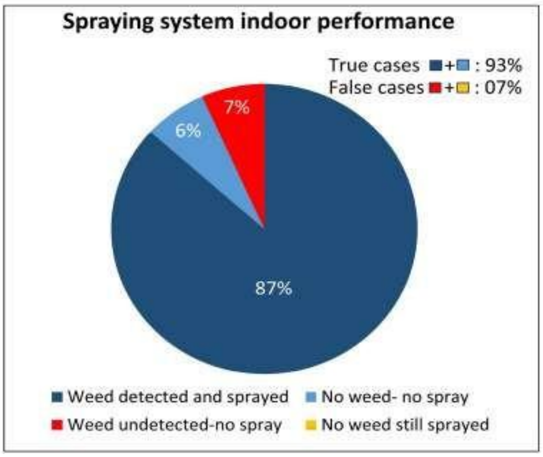
2. **Data processing and augmentation:** Raw images often require preprocessing steps such as radiometric and atmospheric corrections, and georegistration to ensure data quality and consistency. A significant challenge in deep learning is the need for large, high-quality training datasets. Data augmentation techniques are frequently employed to expand existing datasets by creating artificial images, which helps improve the robustness and generalization ability of DL models. Physically-grounded data augmentation, which simulates realistic sensor and environmental variations, is often preferred over naive computer vision techniques to avoid creating physically impossible data Fraccaro *et al.,* 2022).

3. **Deep learning model architectures:** Various deep learning architectures have been successfully applied to weed detection tasks. These can be broadly categorized into object detection, image segmentation, and image classification models

Object detection models: These models identify and locate weeds within an image by drawing bounding boxes around them. Popular models include You Only Look Once (YOLO) and Faster R-CNN (Saleem *et al*., 2022).

Image segmentation models: These models provide pixel-wise classification, delineating the exact boundaries of weeds from crops and the background. This level of detail is critical for precise herbicide application or mechanical removal **U-Net and U-Net++, Mask RCNN.**

Image classification models: These models classify an entire image or specific regions as containing weeds or crops. While less precise for localized control, they are foundational for broader weed presence assessment. Convolutional Neural Networks (CNNs) are the backbone of most deep learning models for imagery, learning hierarchical spatial features by applying filters. Architectures like ResNet and VGG-16 have been used for classifying and segmenting canola plants, demonstrating their utility in distinguishing crops from weeds (Mckay *et al*., 2024).



Source: (Upadhyay *et al.,* 2024)

4. **Detection and actuation:** The outputs from these deep learning models (e.g., bounding boxes, segmentation masks) are then used to inform actuation systems in smart agricultural machinery. This can include robotic sprayers that apply herbicides only to identified weed patches, or robotic systems capable of mechanical weed removal. For example, a smart spraying system utilizing a machine vision and deep learning approach has been designed for precise spray application onto target weeds. Robotic weed spot-spraying has shown promise in significantly reducing herbicide usage on farms (Azghadi *et al*., 2024).

Challenges and future directions

Despite significant advancements, several challenges remain in the widespread adoption of deep learning for weed management:

Data variability and scarcity: Acquiring diverse and large-scale datasets that cover various crop types, weed species, growth stages, lighting conditions, and environmental factors is critical. The visual similarity between crops and weeds, especially at early growth stages ("green-on-green" problem), further complicates detection.

Real time performance: Deep learning models, especially complex ones, require substantial computational resources. Deploying these models on edge computing devices for real-time operation in the field demands optimization for inference speed without compromising accuracy.

Generalization across the environment: Models trained in one environment may not perform optimally in different geographical locations or under varying environmental conditions due to domain shift. Cross-domain transfer learning and adaptive frameworks are being explored to address this.

Integration with robotics: Seamless integration of deep learning models with robotic platforms for autonomous navigation, precise targeting, and mechanical removal requires sophisticated software and hardware coordination.

Future research directions include developing more robust models that can handle the interclass similarity between weed species and intra-class dissimilarity due to different growth stages. The integration of transformer topologies with CNNs in models like YOLO and Mask R-CNN is a promising avenue for improving performance. Furthermore, exploring advanced drone-based weed detection using feature-enriched deep learning approaches with modified backbone, neck, and head components leveraging elements like Ghost Convolution and Efficient Channel Attention layers could achieve optimal performance. The development of adaptive deep learning frameworks for weed species classification, such as ADeepWeeD, is also critical for efficient weed management.

CONCLUSION:

deep learning is revolutionizing weed management by offering precise, automated, and sustainable solutions that can significantly reduce herbicide use and improve agricultural productivity. While challenges remain, continuous innovation in model architectures, data aquicision and hardware integration is paving the way for smarter farming practices globally.

REFERENCES:

Aerial Vehicles Imagery. Remote Sensing, 14(17), 4197. https://doi.org/10.3390/rs14174197

Aerial Vehicles Imagery. Remote Sensing, 14(17), 4197. https://doi.org/10.3390/rs14174197

Agriculture and Food Research, 18, 101331. https://doi.org/10.1016/j.jafr.2024.101331

Azghadi, M. R., Olsen, A., Wood, J., Saleh, A., Calvert, B., Granshaw, T., Fillols, E., & Enhancing Environmental Outcomes in Sugarcane. arXiv. https://doi.org/10.48550/ARXIV.2401.13931

Fraccaro, P., Butt, J., Edwards, B., Freckleton, R. P., Childs, D. Z., Reusch, K., & Comont, D. (2022). A Deep Learning Application to Map Weed Spatial Extent from Unmanned

Fraccaro, P., Butt, J., Edwards, B., Freckleton, R. P., Childs, D. Z., Reusch, K., & Comont, D. (2022). A Deep Learning Application to Map Weed Spatial Extent from Unmanned

Gao, J., Liao, W., Nuyttens, D., Lootens, P., Xue, W., Alexandersson, E., & Pieters, J. (2024). Cross-domain transfer learning for weed segmentation and mapping in precision farming using ground and UAV images. Expert Systems with Applications, 246, 122980. https://doi.org/10.1016/j.eswa.2023.122980

Identification for Precision Weed Management Using Deep Learning. Remote Sensing, 16(11), 2041. https://doi.org/10.3390/rs16112041

Keerthi, T.Bhavya Sai. (2025). AgroWeedGuard : Smart Weed Detection for a healthier Harvest using CNN and Deep Learning. INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT, 09(02), 1–9. https://doi.org/10.55041/ijsrem41603

Mckay, M., Danilevicz, M. F., Ashworth, M. B., Rocha, R. L., Upadhyaya, S. R., Bennamoun, M., & Edwards, D. (2024). Focus on the Crop Not the Weed: Canola Identification for Precision Weed Management Using Deep Learning. Remote Sensing, 16(11), 2041. https://doi.org/10.3390/rs16112041

Mckay, M., Danilevicz, M. F., Ashworth, M. B., Rocha, R. L., Upadhyaya, S. R., Bennamoun, M., & Edwards, D. (2024). Focus on the Crop Not the Weed: Canola

Murad, N. Y., Mahmood, T., Forkan, A. R. M., Morshed, A., Jayaraman, P. P., &

Siddiqui, M. S. (2023). Weed Detection Using Deep Learning: A Systematic Literature Review. Sensors, 23(7), 3670. https://doi.org/10.3390/s23073670

Philippa, B. (2024). Precision Robotic Spot-Spraying: Reducing Herbicide Use and

Rahman, M. G., Rahman, M. A., Parvez, M. Z., Patwary, M. A. K., Ahamed, T., FlemingMuñoz, D. A., Aloteibi, S., & Moni, M. A. (2025). ADeepWeeD: An adaptive deep learning framework for weed species classification. Artificial Intelligence in Agriculture, 15(4), 590–609. https://doi.org/10.1016/j.aiia.2025.04.009

Saleem, M. H., Potgieter, J., & Arif, K. M. (2022). Weed Detection by Faster RCNN Model: An Enhanced Anchor Box Approach. Agronomy, 12(7), 1580. https://doi.org/10.3390/agronomy12071580

Sandoval-Pillajo, L., García-Santillán, I., Pusdá-Chulde, M., & Giret, A. (2025). Weed detection based on deep learning from UAV imagery: A review. Smart Agricultural Technology, 12, 101147. https://doi.org/10.1016/j.atech.2025.101147

Upadhyay, A., G C, S., Zhang, Y., Koparan, C., & Sun, X. (2024). Development and evaluation of a machine vision and deep learning-based smart sprayer system for sitespecific weed management in row crops: An edge computing approach. Journal of

Vasileiou, M., Kyrgiakos, L. S., Kleisiari, C., Kleftodimos, G., Vlontzos, G., Belhouchette, H., & Pardalos, P. M. (2024). Transforming weed management in sustainable agriculture with artificial intelligence: A systematic literature review towards weed identification and deep learning. Crop Protection, 176, 106522. https://doi.org/10.1016/j.cropro.2023.106522 Zhao, H., & Wang, Y. (2026). Deep learning–based approaches for weed detection in crops. Frontiers in Plant Science, 16. https://doi.org/10.3389/fpls.2025.1746406.