IJARCCE

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.155268

Design And Implementation of An Embedded CNN based Weed Detection and Mechanical Weed Elimination Rover

Sai Badgujar[1], Raj Patil[2], Gaurav Shinde[3], Parth Borgude[4], Rupali Shirsath[5], Prof. Mayur Kumbharde[6]

[1,2,3,4,5,6] Department of Artificial Intelligence and Data Science Engineering, SNJB's Late Sau. K. B. Jain College of Engineering, Chandwad, Nashik, Maharashtra, India.

Abstract: Weed invasion remains a significant challenge in modern agriculture, contributing to reduced crop productivity and increased operational costs. Conventional weed control practices, including manual weeding and chemical herbicide application, are labour-intensive and raise environmental and health concerns. This study presents the development, implementation, and experimental assessment of an embedded deep learning system based on computer vision for identifying weeds and removing them mechanically using a mobile robotic platform.

The proposed system employs a Convolutional Neural Network (CNN) deployed implemented on a compact embedded device like the Raspberry Pi to perform on-device weed detection from camera-acquired field images. Detected weeds are localized and processed in real time to guide a servo-driven mechanical plucking mechanism, enabling physical weed removal without the use of chemical herbicides. The system integrates visual perception, embedded processing, rover mobility, and mechanical actuation into a compact and low-cost platform intended for small- and medium-scale agricultural settings.

Experimental evaluation was conducted under controlled and limited real-field conditions to assess detection performance and system feasibility. The outcome indicate that the developed system can successfully identify weeds and perform targeted mechanical removal while operating within the computational constraints of embedded hardware. These findings demonstrate the capability of embedded deep learning robotic systems to support precise and chemical-free weed control solutions.

Keywords: Weed Detection, Convolutional Neural Networks, Precision Agriculture, Agricultural Robotics, Autonomous Rover, Edge AI, Mechanical Weed Removal.

I. INTRODUCTION

Weed invasion continues to be a major challenge in modern agriculture, because weeds compete with crops for water, nutrients, sunlight, and space, which reduces crop yield and increased production costs. Conventional weed control methods primarily rely on manual labour and chemical herbicides. Manual weed removal requires a lot of labor and takes a significant amount of time., while extensive herbicide use raises concerns related to environmental impact and occupational health.

In recent years, growing awareness of these concerns has encouraged the development of alternative weed management strategies that reduce chemical dependency. Advances in computer vision, deep learning, and embedded systems have enabled intelligent agricultural solutions capable of identifying weeds under real field conditions. Convolutional Neural Network (CNN)–based approaches have shown improved robustness compared to traditional image processing methods, particularly in complex and unstructured environments.

Motivated by these developments, this work presents the development and testing of an embedded CNN-based system for weed detection and mechanical removal system using a mobile robotic rover. The proposed system performs on-device weed detection using embedded edge hardware and executes camera-guided mechanical weed removal, with rover movement supervised through a mobile application. The approach aims to provide a low-cost and chemical-free solution suitable for small- and medium-scale farming environments and serves as a foundation for future advancements in agricultural robotics.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.155268

II. LITERATURE SURVEY

Early weed detection systems mainly depended on traditional image processing methods such as color segmentation, thresholding, and morphological operations. These approaches required manually engineered features and were highly affected by changes in lighting, soil texture, and background conditions, which reduces their reliability in real field environments.

Latest studies have increasingly used deep learning methods, especially Convolutional Neural Networks (CNNs), for weed classification, detection, and segmentation. CNN-based approaches automatically learn discriminative visual features from data and have demonstrated improved robustness and accuracy compared to traditional techniques. When integrated with robotic platforms, such methods enable selective weed management. However, many existing systems continue to rely on chemical spraying, limiting their environmental benefits.

Advances in artificial intelligence and embedded computing have further supported the deployment of vision-based weed detection on resource constrained platforms using models such as YOLO, ResNet, and MobileNet. In parallel, agricultural robotics has enabled automated weeding solutions; however, many commercially available systems are expensive, chemically dependent, or require tractor mounted operation, reducing their suitability for small- and medium-scale farms.

Based on literature reviews, remains a need for low-cost, embedded, and mechanically actuated weed removal systems that operate without chemical herbicides. This identified gap motivates the development of the system presented in this work.

Limitations of Existing Work

Despite progress in AI-based weed detection and agricultural robotics, several practical limitations remain. Many existing systems require substantial computational resources, which limits real-time deployment on low-power embedded platforms. In addition, a large proportion of current approaches continue to rely on chemical spraying, raising ongoing environmental and health concerns. Detection performance often degrades in real field conditions due to variations in crop appearance, soil texture, illumination, and background complexity. Furthermore, the lack of large, diverse, and properly annotated agricultural datasets limits the ability of trained models to generalize effectively. These limitations highlight the need for lightweight, embedded, and chemical-free weed management systems suitable for dynamic agricultural environments.

TABLE 1: LITERATURE-BASED COMPARISON OF AI MODELS FOR REAL-TIME WEED DETECTION

Algorithm Category	Representative Models	Detection Capability	Inference Characteristics	Computational Demand	Suitability for Real -Time Embedded Use
Traditional Image Processing	Color segmentation, morphology	Limited robustness in complex scenes	Fast on simple hardware	Very low	Low (high sensitivity to field variation)
CNN-Based Classification	ResNet, MobileNet	Accurate image – level classification	Moderate	Medium	Limited (no spatial localization)
Two-Stage Object Detection	Faster R-CNN	High detection accuracy with localization	Slow inference	High	Poor (computationally intensive)
One-Stage Object Detection	YOLO, SSD	Simultaneous detection and localization	Fast inference	Medium	High
Semantic Segmentation	U-Net, DeepLab	Pixel-level classification	High latency	Very high	Low (real time constraints)
Lightweight Detection Models	YOLO-Tiny, MobileNet-SSD	Balanced accuracy and speed	Fast inference	Low	High (suitable for Edge AI)

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⫶ Peer-reviewed & Refereed journal ⫶ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.155268

III. SYSTEM DESIGN AND IMPLEMENTATION

The proposed system presents a vision-based framework for weed detection and mechanical removal using an embedded robotic rover. It integrates deep learning–based image processing with an embedded hardware platform to enable targeted, chemical-free weed management in agricultural fields.

The primary objective of the system is to reduce manual labour and minimize reliance on chemical herbicides while improving precision in weed control. A camera mounted on the mobile rover continuously captures field images, which are processed using a Convolutional Neural Network (CNN) is trained to identify weeds and crops. The trained model is then implemented on an embedded edge device for real-time detection and processing. When a weed is detected, its location is estimated using image-based coordinates, and corresponding control signals are generated for the actuation mechanism. A servo-driven mechanical plucking unit is then guided toward the detected location to perform physical weed removal. Rover movement is achieved using DC motors and is supervised through a mobile application interface, while all system components are powered by an onboard battery.

Overall, the system combines embedded vision-based detection, edge processing, controlled rover mobility, and mechanical actuation into a compact robotic platform. The proposed design addresses key limitations of existing weed management approaches by enabling selective, non-chemical weed removal on resource-constrained embedded hardware.

Table 2: Comparison of Existing Systems and the Proposed Framework

Feature	**Existing Systems**	**Proposed System**
Weed Removal Mechanism	Chemical Spraying / Laser based methods	Mechanical plucking using a robotic actuator
Cost Characteristics	Generally, high due to complex hardware and maintenance	Low-cost implementation using commercially available components
Chemical Usage	Often dependent on herbicides	Non-chemical mechanical weed removal
Farm Suitability	Commonly designed for large scale operations.	Intended for small- to medium-scale farms
Deployment	Bulky or tractor mounted systems	Compact and mobile robotic rover
Tractor Dependency	Frequently requires tractors or external machinery	Standalone rover-based platform
Power Source	High power consumption systems	Battery-powered embedded system
Scalability	Limited by cost and system complexity	Adaptable and scalable with modular design

IV. SYSTEM ARCHITECTURE

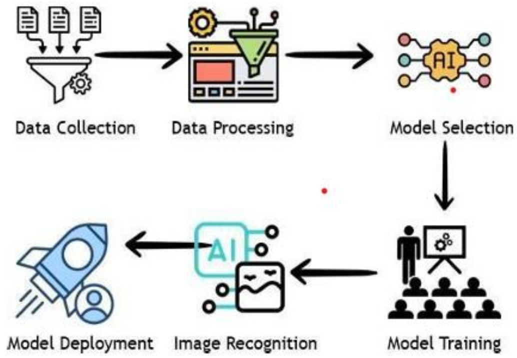
The proposed weed detection and removal system follows a dual-architecture design consisting of a **model training architecture** and a **hardware implementation architecture**. This separation allows independent development, evaluation, and deployment of the vision model and the embedded robotic platform.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.155268



A. Model Training Architecture

The model training architecture focuses on developing deep learning models capable of distinguishing weeds from crops using image data captured under real field conditions. Images of agricultural fields containing both weeds and crops are collected and used as the primary dataset for training and evaluation.

The collected images undergo preprocessing steps including resizing, normalization, and data augmentation techniques such as rotation, flipping, and brightness adjustment to improve robustness and generalization.

The dataset is manually annotated using bounding boxes to label weed and crop regions, enabling supervised learning.

Two types of models are trained in this work: a YOLO-based object detection model for weed localization and a MobileNet-based convolutional neural network for image-level classification. Model training is performed using standard optimization techniques, and performance is evaluated on a holdout test set. The trained models are then exported in an optimized format suitable for deployment on embedded hardware.

B. Hardware Architecture

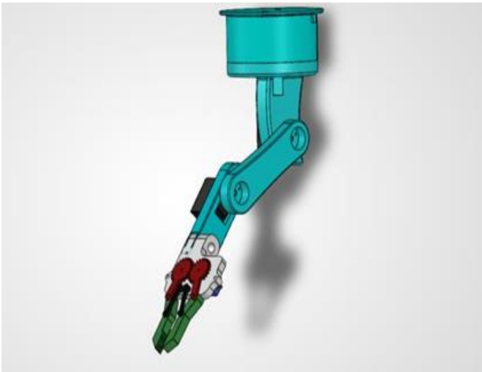
The hardware architecture implements the trained detection model on a mobile rover platform designed for field operation. A dual-processor configuration is adopted, where a Raspberry Pi 5 performs image processing and inference tasks, while an ATmega2560-based Arduino Mega handles low-level motor and actuator control.
The rover is powered by a 12 V battery, with buck converters providing regulated voltage to system components. Locomotion is achieved using DC gear motors driven by BTS7960 H-bridge motor drivers. A Raspberry Pi Camera module continuously captures visual data, which is processed on-device to detect weeds.

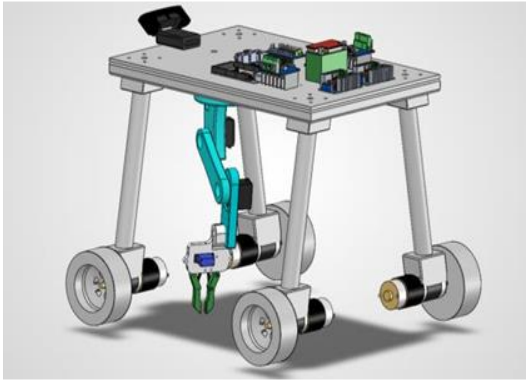
IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 5, May 2026

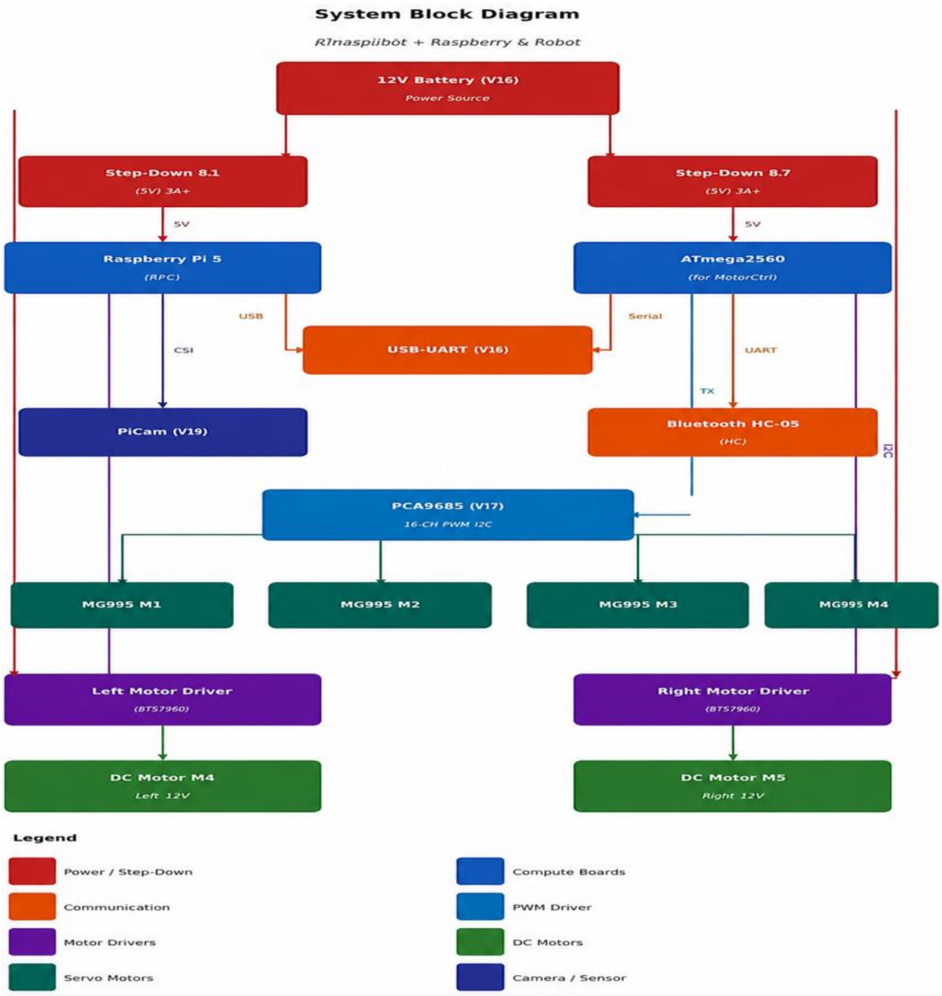
DOI: 10.17148/IJARCCE.2026.155268





When a weed is detected with a confidence score exceeding a predefined threshold, control signals are generated to activate the mechanical removal mechanism. Actuation is performed using servo motors controlled via a PCA9685 PWM driver. The weed removal unit consists of a 3D-printed mechanical arm designed for physical extraction of weeds. Communication between the Raspberry Pi and Arduino Mega is established through a USBUART interface to ensure coordinated perception and actuation.

This modular hardware design supports reliable operation on embedded hardware and allows future upgrades to sensing, actuation, and control modules.



V. DATASET PREPARATION AND MODEL TRAINING

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.155268

A. Dataset Description

A self-collected dataset was created for this study to ensure relevance to real agricultural conditions. The dataset consists of **1,250 images**, including **900 images containing weeds** and **350 images containing crops**, captured under varying lighting and background conditions.

All images were manually annotated using the Labeling annotation tool. Bounding boxes were assigned to label weed and crop regions, enabling supervised learning for both object detection and classification tasks. The dataset was divided into training and testing sets using a 75:25 split, providing sufficient data for model training and independent performance evaluation.

B. Model Training Details

Two different deep learning approaches were trained and evaluated:

1. MobileNet-based CNN

2. YOLO-based object detection models

Model training was conducted using **Google Colab** and a **local GPU-enabled system** to accelerate computation. The MobileNet-based CNN was trained for **50 epochs**, achieving high classification accuracy with stable convergence between training and validation phases, indicating effective feature learning for weed–crop discrimination.

The YOLO-based object detection models were trained for **100 epochs** using the annotated dataset. Training was configured to balance detection accuracy with deployment feasibility on embedded hardware platforms.

V. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

This section presents the experimental evaluation of the proposed weed detection system using two deep learning models: a YOLO-based object detection model and a MobileNet-based CNN classifier. The models were trained using a self-collected dataset and evaluated under offline experimental conditions.

A. YOLO-Based Weed Detection Results

The YOLOv8 model was tested using a validation dataset of 240 images containing 204 weed samples. The results show that the model achieves high detection accuracy and performs well in identifying weeds under different conditions.

Table 3: YOLOv8 Detection Performance **Table 4: YOLOv8 Model Efficiency**

Metric	Value
Precision	96.8%
Recall	86.3%
F1-score	91.2%
mAP@0.5	95.5%
mAP@0.5-0.9	89.2%

DOI: 10.17148/IJARCCE.2026.155268

Parameter	**Value**
Model Variants	YOLOv8n
Parameters	~3.0 million
Model Size	~6.2 MB
FLOPs	~8.1GFLOPs
Inference Speed (GPU)	~1.9ms/images

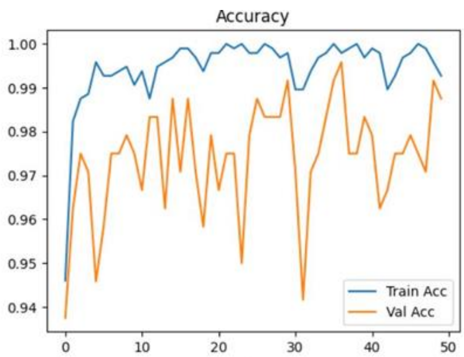
The lightweight architecture and small model size make YOLOv8 appropriate for implementation on embedded edge devices like the Raspberry Pi.

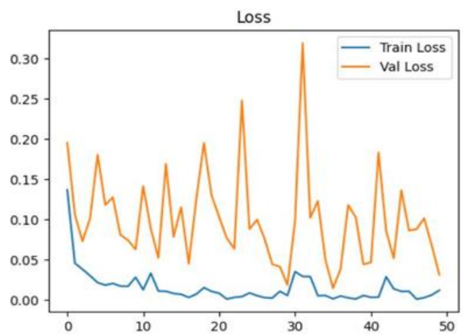
B. The MobileNet-based CNN model was trained to classify weeds accurately, using the same self-collected dataset. The model was trained for 50 epochs using GPU.

Table 5: MobileNet Classification Performance

Metric	Training	Validation
Accuracy	99.29%	98.75%
Loss	0.0111	0.0317
Epochs	-	50

The MobileNet model achieved high classification accuracy with low validation loss, indicating good generalization and stable training behavior. Due to its lightweight nature, MobileNet is well suited for low-power embedded systems where classification-based weed identification is sufficient.





C. Comparative Analysis

Table 6: Comparison Between YOLOv8 and MobileNet Models

Aspect	**YOLOV8**	**MobileNet**
Task Type	Object Detection	Image Classification
Output	Bounding Boxes + class	Weed / Crop label
Precision	Very High	High
Localization Capability	Yes	No
Model Size	Small	Very Small
Suitability for Robotics	Excellent	Moderate

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 15, Issue 5, May 2026

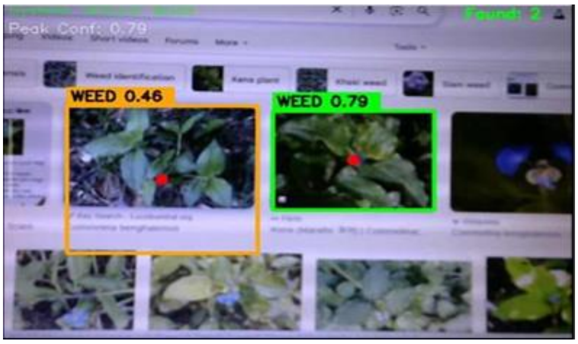
DOI: 10.17148/IJARCCE.2026.155268

YOLOv8 provides precise localization required for mechanical weed removal, while MobileNet offers efficient classification with lower computational complexity. Therefore, YOLOv8 is more suitable for autonomous weed removal tasks involving spatial actuation.

D. Discussion

The experimental results indicate that CNN-based weed detection models can achieve promising performance when trained on a relatively small, selfcollected dataset. The YOLOv8 model shows advantages for robotic applications due to its ability to provide both detection and localization, while the MobileNet-based model offers a lightweight alternative for image-level weed classification. Overall, the findings suggest that deploying deep learning–based weed detection on embedded agricultural robotic platforms is feasible under controlled experimental conditions.

E. YOLOv8-Based Weed Detection Implementation In the final implementation, the weed detection module was developed using a YOLOv8-based object detection model due to its ability to perform simultaneous weed classification and localization in a single processing step. This characteristic makes the model suitable for vision-guided robotic applications requiring spatial information for actuation on embedded and edge-based platforms. The trained YOLOv8 model was converted into ONNX (Open Neural Network Exchange) format to enable platform-independent deployment and efficient operation on the embedded system. The ONNX representation enables optimized execution with reduced computational overhead while preserving detection performance.



VI. FUTURE SCOPE

Although the proposed system demonstrates the feasibility of vision-based weed detection and mechanical removal on embedded hardware, several enhancements can be explored to improve performance and applicability. Future work may investigate alternative power sources, such as solarassisted charging, to extend operational duration and reduce dependence on battery recharging.

Additional sensing and navigation capabilities, including ultrasonic sensors or vision-based path planning, can be integrated to improve mobility and obstacle avoidance in complex field environments. Detection performance can be improved further by increasing the training dataset and using advanced techniques such as transfer learning and better object detection models. Furthermore, the system can be adapted for multicrop scenarios to support broader agricultural applications. Refinements in mechanical design and actuation may improve durability and operational reliability, providing a more robust platform for extended field use.

VII. CONCLUSION

This work presents the design and implementation of an embedded vision-based system for weed detection and mechanical removal using a mobile robotic platform. By employing a YOLOv8-based deep learning model, the system enables image-based weed detection and localization, which is used to guide a servo-driven mechanical plucking mechanism for targeted weed removal without chemical herbicides. The proposed system integrates a Raspberry Pi, camera module, and embedded control hardware to provide a compact and low-cost solution intended for small- and medium-scale agricultural applications. Experimental evaluation demonstrates the feasibility of combining deep learning–based perception with mechanical weed removal on embedded hardware. While system performance may be influenced by environmental factors such as lighting conditions, terrain variability, and power constraints, the proposed platform provides a practical basis for further research and development in robotic weed management.

DOI: 10.17148/IJARCCE.2026.155268

ACKNOWLEDGEMENT

The authors sincerely thanks **SNJB's Late Sau. K. B. Jain College of Engineering, Chandwad,** for providing the academic support and infrastructure required for this research work. They also appreciate the valuable guidance and suggestions offered by the faculty members of the **Department of Artificial Intelligence and Data Science Engineering**, which helped improve the quality of this work. The authors are also grateful to their peers and everyone who contributed to this study, either directly or indirectly.

REFERENCES

[1] M. Murad, A. Khan, and S. Khan, "Weed Detection Using Deep Learning: A Systematic Literature Review," Sensors, vol. 23, no. 7, pp. 134, 2023.

[2] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning techniques for in-crop weed recognition in large-scale grain production systems: A review," Precision Agriculture, vol. 25, no. 2, pp. 456–489, 2024.

[3] R. Sonawane and P. Patil, "Comparative analysis of YOLO object detection models for weed detection," Smart Agricultural Technology, vol. 5, pp. 100312, 2024.

[4] A. Hasan, M. Ahmad, and S. Abdullah, "Applications of deep learning in precision weed management: A review," Computers and Electronics in Agriculture, vol. 203, pp. 107471, 2023.

[5] Y. Liu et al., "Field-based multispecies weed and crop detection using advanced YOLO models," Smart Agricultural Technology, vol. 6, pp. 100398, 2024.

[6] Z. Wang et al., "ADL-YOLOv8: A field crop weed detection model based on improved YOLOv8," Agronomy, vol. 14, no. 2, pp. 412–428, 2024.

[7] H. Zhang et al., "Early weed identification based on deep learning: A review," Smart Agricultural Technology, vol. 4, pp. 100267, 2023.

[8] M. Hasan et al., "Deep learning for in-crop weed detection: A survey," Computers and Electronics in Agriculture, vol. 180, pp. 105889, 2021.

[9] S. Badgujar, P. Patil, and R. Sonawane, "You Only Look Once (YOLO) object detection literature review for agricultural applications," arXiv preprint arXiv: 2403.XXXXX, 2024.

[10] A. Kumar et al., "Architecture and hyperparameter optimization of YOLOv5 and YOLOv8 for garlic weed detection," Scientific Reports, vol. 16, pp. 1–15, 2026.

[11] A. Olsen et al., "DeepWeeds: A multiclass weed species dataset for deep learning," Scientific Reports, vol. 9, no. 2058, 2019.

[12] J. Li et al., "Weed detection using deep learning in complex and occluded potato fields," Crop Protection, vol. 178, pp. 106564, 2024.

[13] M. Rahman et al., "Comparison of RetinaNet, Faster R-CNN, and YOLO models for weed detection," Machines, vol. 13, no. 3, pp. 219, 2025.

[14] S. Sladojevic et al., "Deep neural networks-based recognition of plant diseases and weeds," Computational Intelligence and Neuroscience, vol. 2016, Article ID 3289801.

[15] A. Dos Santos Ferreira et al., "Weed detection in soybean crops using UAV imagery and deep learning," Remote Sensing, vol. 12, no. 5, pp. 1–18, 2020.

[16] J. Chebrolu et al., "Agricultural robot dataset for weed and crop detection," International Journal of Robotics Research, vol. 40, no. 4–5, pp. 521–528, 2021.

[17] M. Partel et al., "Towards practical object detection for weed spraying in precision agriculture," Frontiers in Plant Science, vol. 14, pp. 1183277, 2023.

[18] L. Bah et al., "Autonomous agricultural robot for weed detection using YOLO-based vision," Machines, vol. 12, no. 11, pp. 801, 2024.

[19] T. Peteinatos et al., "Laser-based robotic weed control systems: A review," Biosystems Engineering, vol. 207, pp. 276–294, 2021.

[20] R. Raja et al., "A two-stage deep learning approach for weed identification in grasslands, Computers and Electronics in Agriculture, vol. 218, pp. 108692, 2024.