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Automated Weed Detection and Classification Using-YOLO

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Abstract- Modern agriculture practice faces increasing pressure to improve productivity while reducing chemical usage and labor dependency. One major challenge is the uncontrolled growth of agriculture weeds, which compete with crops for essential resources and significantly reduce yield. This paper presents an automated weed detection and classification system built using the YOLOv8 architecture. The model is trained on annotated crop-field images containing both crop and weed categories. The system aims to deliver real-time identification with high accuracy, enabling selective herbicide spraying and automated monitoring. The work integrates image preprocessing, model training, validation, and deployment in a practical pipeline. Experimental results demonstrate strong detection performance, reliable bounding-box prediction, and robust generalization under varied lighting and field conditions. The proposed method highlights an effective direction for precision agriculture and supports sustainable farming practices.

Keywords: Weed Detection, YOLOv8, Deep Learning, Precision Agriculture, Computer Vision, Sustainable Farming.

I. INTRODUCTION

Weeds are one of the most persistent threats to agricultural productivity. They compete with crops for nutrients, water, light, and soil space, causing substantial yield loss. Traditional weed control methods rely heavily on manual labor or broad-spectrum herbicide spraying, both of which are costly, time-consuming, and environmentally harmful. With the growth of precision agriculture, computer-vision-based weed detection has become an essential tool for modern farms.

In recent years, deep learning—especially convolutional neural networks—has transformed image-based classification tasks. Among these, the You Only Look Once family stands out for its speed and accuracy in real-time detection. This (YOLO) approach processes a single image in a single pass, making it ideal for on- field agricultural practices such as weed monitoring. This research develops a system that applies the YOLO architecture to detect and classify weeds in agricultural fields. The objective is to provide farmers with a reliable, automated method to reduce chemical spraying, prevent crop damage, and optimize field management.

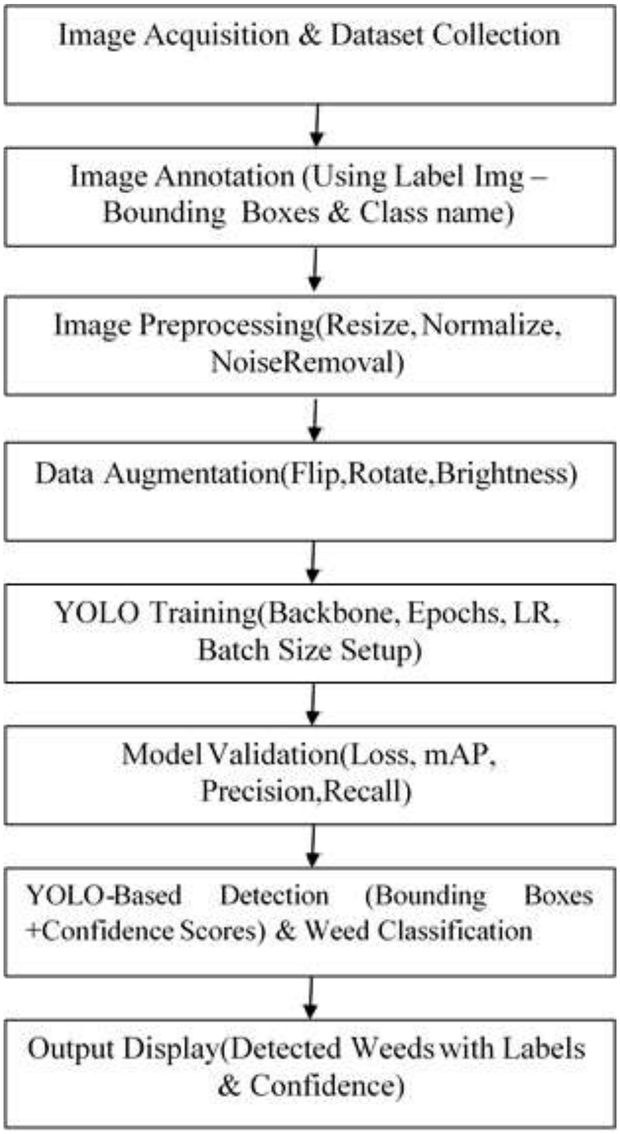
II. LITERATURE REVIEW

Deep-learning-driven weed detection has matured considerably due to improved computational power and availability of labelled datasets. The Earlier approaches relied on handcrafted features such as texture, color, or edge patterns for discrimination. While effective in small scenarios, these techniques failed under variable environmental conditions.

Recent studies employ object detection frameworks such as Faster R-CNN, SSD, and YOLO. Models like Faster R CNN provide strong accuracy but are computationally heavy, reducing their real-time usability. On the other hand, YOLO-based frameworks have demonstrated notable efficiency for drone-based crop imaging, row-crop weed detection, and selective spraying systems. Most works emphasize the need for more useful systems capable of performing well in diverse lighting conditions, soil backgrounds, and weed shapes. This motivates developing a robust YOLO-based pipeline that can generalize across field variations.

III. PROPOSED SYSTEM

Flow Chart



Data Collection

Images of crop fields are gathered using mobile cameras and drone sources. Multiple weed types and crop growth stages are captured to ensure dataset diversity. The Field images are collected by considering the different lighting conditions, soil textures, and weed densities.

Field Image Captured for Weed Detection

Data Annotation

Each image is manually labelled using tools such as LabelImg to mark crop and weed objects. Bounding boxes are created and assigned appropriate class labels. These annotated samples are then exported in YOLO-compatible format.

Preprocessing

Before training, images undergo resizing, normalization, and augmentation. Operations such as random rotation, horizontal flipping, brightness adjustment, and perspective distortion help the model handle real- field variability.

Model Architecture

The detection model is based on the YOLO_v8 framework, having a light-weight structure and fast inference. It divides each image into a smaller part called grids &predicts bounding boxes along with class probabilities. YOLOv8’s improved backbone and neck design enhances feature extraction &reduce false detections.

Training Process

This model is trained using a GPU environment. The included parameters include batch size, learning rate, optimizer selection, and number of epochs. Loss functions combine localization, objectness, and classification errors to guide learning.

Output Generation

During inference, the system outputs images with bounding boxes, confidence scores, and class labels. These results can be integrated into farming robots, drone dashboards, or mobile applications.

Results of the Inferenced Images

Table

SL.NO	Weed Type	Weed Name	Images per Weed
1	Invasive	Parthenium Hysteroporous	1500
2	Broadleaf	Amaranthus palmer & Chenopodium album	1500 each Total=3000
3	Grass	hinocloa colona & Lolium perenne	1500 each Total=3000

IV. RESULTS AND DISCUSSION

The trained model shows strong performance in detecting multiple weed types at different growth stages. High-confidence predictions indicate efficient learning the differences between crop plants and weeds. Even in cluttered backgrounds, the system maintains stable accuracy due to augmentation and diverse training images.

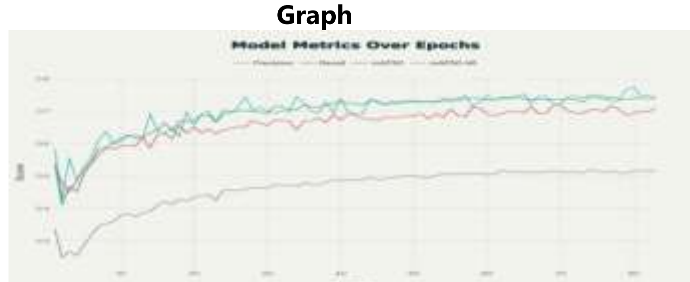
Precision and recall metrics demonstrate balanced performance, ensuring that the model does not miss weeds while also minimizing false detections. Validation experiments under sunlight variation, shadows, and mixed vegetation confirm that the approach generalizes well.

Performance can be enhanced further by expanding the dataset, training on region-specific weed categories, and integrating multispectral imaging.

Table

Metric	Description	Observation
ModelType	YOLOv8	Used for real time-weed detection
Dataset Size	Customweed dataset	Contains multiple weed species
Detection Output	Bounding box+Label+Confidence	Correct weed identification

Graph



V. APPLICATIONS

Smart Spraying Systems
The system can guide automated sprayers to target only the areas where weeds exist, reducing excessive herbicide usage.

Drone-Based Surveillance
Drones equipped with cameras and YOLO models can cover large fields quickly for real-time weed mapping.
Mobile Agriculture Assistants

Farmers can use smartphones with the integrated detection model to instantly identify weed presence in fields.

Autonomous Farming Robots
Robots can extract, remove, or treat weeds without human intervention using onboard weed-detection intelligence.

VI. CONCLUSION

This research presents a fully automated weed detection and classification system utilizing the YOLO deep- learning architecture. The system demonstrates strong detection capability, real-time processing, and reliable classification accuracy under diverse agricultural conditions. It supports precision agriculture by reducing manual labor, minimizing chemical usage, and improving crop health. The study indicates that deep- learning-based weed detection is a critical step toward sustainable and technologically advanced farming practices.

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