Deep Learning-Based Weed Detection for Sustainable Agriculture

1 ABSTRACT

This study presents a semi-supervised learning model based on YOLOv9(You Only Look Once) to address the critical challenge of weed detection in precision agriculture. By leveraging the robust object detection capabilities of YOLOv9 and a carefully designed semi-supervised framework, the proposed approach achieves high classification accuracy while reducing dependency on labeled data. Key evaluation metrics, including confidence scores, F1 scores, and Generalized Intersection over Union (GIoU), were used to assess model performance. The results demonstrate the effectiveness of the proposed method in achieving accurate weed detection and sustainable farming practices.

2 INTRODUCTION

Weed detection is a fundamental challenge in precision agriculture, where traditional methods relying on chemical herbicides have significant environmental and economic impacts. Deep learning models, particularly YOLO-based architectures, have gained popularity for their real-time object detection capabilities. However, fully supervised approaches often require extensive labeled data, which can be expensive and time-consuming to obtain. To overcome this limitation, we propose a semi-supervised learning model utilizing YOLOv9 to improve weed detection performance while minimizing data annotation efforts.

The initial dataset consisted of 200 labeled and 1,000 unlabeled images containing crops and weeds. The semi-supervised learning approach began by training the YOLOv9 model on the 200 labeled images. Subsequently, 1,000 unlabeled images were introduced, and the most reliable pseudo-labeled samples are selected. These selected images were in- corporated into the training process, and the modelwas iteratively retrained using the entire unlabeled dataset. This iterative process generated a pseudo-labeled dataset, significantly enhancing prediction accuracy

3 METHODOLOGIES AND IMPLEMENTATIONS

3.1 Data Augmentation

Augmentation is essential for weed detection as it helps the model generalize better to diverse field conditions, enhances its ability to distinguish crops from weeds under challenging visual environments, and reduces the risk of overfitting.

We have employed the Albumentations library for data augmentation, applying transformations such as RandomBrightnessContrast, HueSaturationValue, RandomFog, RandomRain, RandomSnow, MotionBlur, GaussianBlur, GaussianNoise, CLAHE, and GridDistortion. For each image, 5 augmented images are generated. These augmentations simulate various environmental conditions like changes in lighting, weather, and image noise, making the model more adaptable to real world scenarios.

3.2 Loss Function

In weed detection, the loss function plays a key role in evaluating how closely the model's predictions match the true labels. It enables the model to learn by penalizing incorrect predictions, driving it to reduce errors over time. For this task, we have utilized the F1 score and GIoU(Generalised Intersection Over Union) loss and YOLOv9 Loss to effectively measure and improve performance. The overall loss is

$$Loss = 0.2 \times (F1.loss) + 0.2 \times (GIoULoss) + 0.6 \times (YOLOLoss)$$

3.2.1 F1 Loss

F1 loss function provides the better evaluation of the performance of the model when false positives and false negatives are of equal importance, which is often the case in real-world scenarios.

The F1 los is calculated using precision and recall, with the F1 score being the harmonic mean of these two metrics. A small epsilon (1e-8) is added to prevent numerical instability and ensure better results.

Precision measures the proportion of positive predictions that are actually correct, while Recall (or sensitivity) gauges the proportion of actual positives that are correctly identified by the model.

By using the harmonic mean, the F1 score prevents misleading outcomes in cases where there is a significant imbalance between precision and recall. It ensures that the model must perform well in both areas to achieve a high F1 score. This makes the F1 score a more reliable overall metric, especially in situations with imbalanced datasets.

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall + 1e-8} \tag{1}$$

3.2.2 GIoU Loss

GIOU (Generalized Intersection over Union) is an enhanced version of the traditional Intersection over Union (IoU), which is widely used to evaluate object detection models. While IoU only focuses on the overlap between the predicted and ground truth bounding boxes, GIOU goes a step further by penalizing the spatial misalignment between them. This enables the model to better localize objects that may not align perfectly with the ground truth, which is crucial for detecting weeds in complex environments. By incorporating GIOU loss, weed detection models can achieve higher precision and recall, resulting in more accurate and reliable weed management for precision agriculture.

$$\mathrm{L}_{GIoU} = 1 - \left(IoU - \frac{|C-(A \cup B)|}{|C|} \right)$$

Here, A and B represent the predicted and ground truth bounding boxes, respectively, while C is the smallest convex shape that encloses both A and B. IoU, on the other hand, is the traditional Intersection over Union metric used to evaluate the overlap between A and B.

3.2.3 YOLOv9 Loss

YOLOv9's loss function enhances previous versions by integrating focal loss for classification and IoU loss for localization. A key innovation is Programmable Gradient Information (PGI), which ensures reliable gradients for optimizing objectness loss, leading to more precise detections and improved performance. It enhances object detection with three key components: bounding box regression, objectness, and classification losses. Bounding box regression ensures precise localization, objectness loss evaluates detection confidence, and classification loss improves label accuracy.

3.3 Confidence Threshold

The confidence threshold in YOLOv9 quantifies the model's certainty in detecting and correctly classifying an object. It is computed as the product of two key components:

(a) **Objectness Confidence** – Represents the probability that an object is present within the predicted bounding box, ranging from 0 to 1.
(b) **Class Confidence** – Indicates the probability that the detected object belongs to a specific class.

$$Confidencethreshold = Objectness \times ClassProbability$$

To generate pseudo-labeled images, a confidence threshold of 0.5 was applied to select the top 200 images after training.

4 RESULTS

Initially, our baseline model, trained solely on labeled data, achieved an F1 score of 0.81 and a mean Average Precision (mAP) at IoU thresholds 50 to 95 (mAP_{50-95}) of 0.582. Implementing semi-supervised learning led to a 10% increase in the F1 score and a 7% rise in mAP_{50-95}, indicating a significant improvement in model performance. The YOLOv9 model achieved high classification accuracy in distinguishing weeds from crops. Key findings include:

- F1 score= 0.89
- mAP50-95= 0.62

The two figures reinforce our findings:

Figure 1 demonstrates the model's ability to accurately detect crops in a sesame field, highlighting its proficiency in identifying cultivated plants.
Figure 2 showcases the model's capability to detect weeds in a sesame field, emphasizing its effectiveness in distinguishing unwanted plants from crops.

5 CONCLUSION

In this study, we achieved the F1 score of 0.89 and mAP50-95 score of 0.62. These metrics indicate that our model is well-balanced and effective in distinguishing between weeds and crops. The training process utilized augmented images, which significantly enhanced the model's ability to accurately identify weeds under various real-world conditions, including cold, snowy, and rainy weather. By generating pseudo-labeled images and incorporating them into the training process of the YOLOv9 model, we were able to further enhance its predictive capabilities. This approach not only bolstered accuracy but also demonstrated the robustness of YOLOv9 for weed detection tasks.

Our findings suggest that YOLOv9 is a promising tool for agricultural applications, particularly in precision farming where timely and accurate weed detection is crucial. Future work could explore the integration of additional environmental factors and the potential for real-time monitoring systems, paving the way for more sustainable agricultural practices. Overall, our research underscores the importance of advanced machine learning techniques in addressing challenges in crop management and enhancing agricultural productivity.

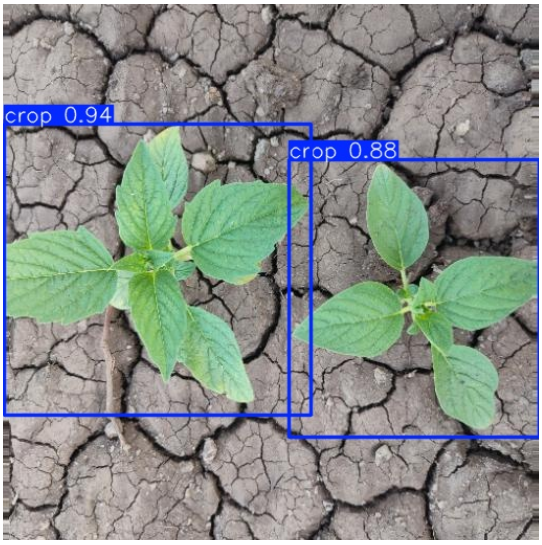

Figure 1. Model Detecting Crops in Sesaeme Field

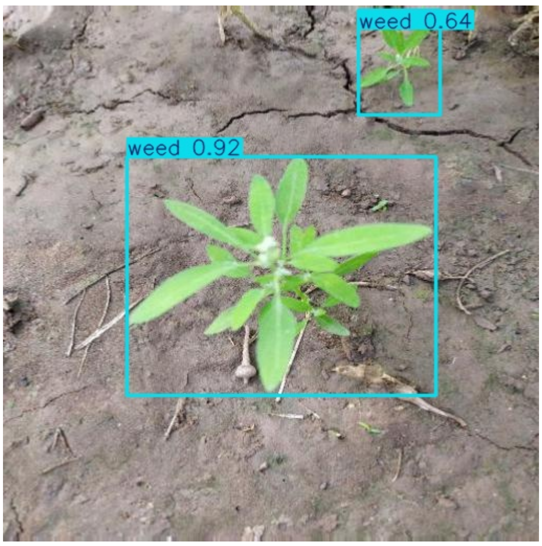

Figure 2. Model Detecting Weeds in Sesaeme Field