Weed Detection Report

Hostel Code - 76

1 Introduction

Weed detection in agricultural fields is crucial for precision farming, reducing herbicide reliance and optimizing crop yields. Traditional supervised learning approaches are limited by the availability of labeled data, making semi-supervised learning techniques an effective alternative. This study employs a combination of supervised and semi-supervised methods to develop a robust weed detection model leveraging YOLO.

2 Dataset Preparation and Preprocessing

Effective dataset preprocessing was crucial given the limited labeled data. We applied transformations to enhance diversity and structured the dataset to suit YOLO-based training.

2.1 Data Augmentation

Rotation (90°, 180°, 270°) and **Horizontal Flipping** improve generalization by exposing the model to varied weed orientations. Bounding boxes were adjusted accordingly.

2.2 Dataset Structuring

Train Set: Augmented labeled images for training. **Dev Set**: Validation set for performance assessment. **Unlabeled Set**: Used in semi-supervised learning.

2.3 YOLO Dataset Format

Images split into **80% training** and **20% validation**. Labels stored in YOLO format (class ID, normalized bounding box coordinates). `data.yaml` file defined dataset paths and categories.

3 Training Methodology

The training process incorporated a sequential combination of supervised and semi-supervised learning techniques.

3.1 YOLOv11m Supervised Training

Trained for **50 epochs** using labeled training data. Configured with batch size **16**, learning rate **5e-5**, and image size **640×640**. GPU acceleration was used via `CUDA`.

3.2 Consistency Regularization

Enforced prediction stability using weak and strong augmentations.

3.3 Pseudo Labeling

Generated high-confidence pseudo labels for unlabeled data.

3.4 FixMatch Algorithm

Used pseudo-labeled data, applying weak and strong augmentations.

3.5 Mean Teacher Model

Both Student and Teacher models were deep copies of FixMatch-trained models. The teacher model guided learning via Exponential Moving Average (EMA).

3.6 Internal Augmentations

During intermediate model training, weak and strong augmentations were applied to maintain labeling consistency. Additionally, since we used Ultralytics for YOLO training, automatic augmentations such as Gaussian blur and color jittering were applied during training.

4 Approach Selection and Insights

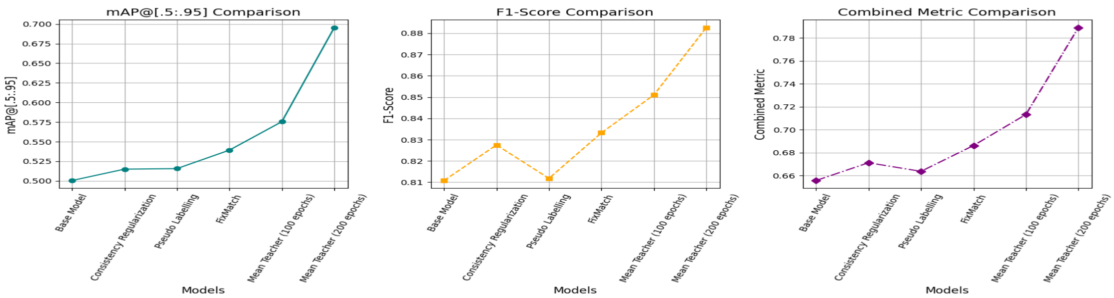
We utilized the Mean Teacher approach with YOLO for semi-supervised learning, where the teacher model generates high-confidence pseudo-labels via Exponential Moving Average (EMA), guiding the student model. To improve robustness, we applied weak and strong augmentations during initial training.

This iterative process, combining pseudo-labeling and EMA, allowed the model to progressively improve using unlabeled data. While precision and recall were initially low, performance improved over time, with visualizing predictions helping refine the model. This approach demonstrated the effectiveness of using unlabeled data for object detection, emphasizing the power of semi-supervised learning.

5 Results and Inferences

Model	Precision	Recall	mAP50	mAP50-95	Fitness	F1 Score	Combined Metric
Base Model	0.8619	0.7655	0.8455	0.5005	0.5350	0.8108	0.6557
Consistency Regularization	0.8078	0.8481	0.8409	0.5150	0.5476	0.8275	0.6712
Pseudo Labeling	0.8027	0.8212	0.8408	0.5157	0.5482	0.8118	0.6637
FixMatch	0.8681	0.8010	0.8541	0.5392	0.5707	0.8332	0.6862
Mean Teacher (100 epochs)	0.8426	0.8596	0.8747	0.5755	0.6054	0.8510	0.7133
Mean Teacher (200 epochs)	0.9175	0.8505	0.9451	0.6956	0.7206	0.8827	0.7892

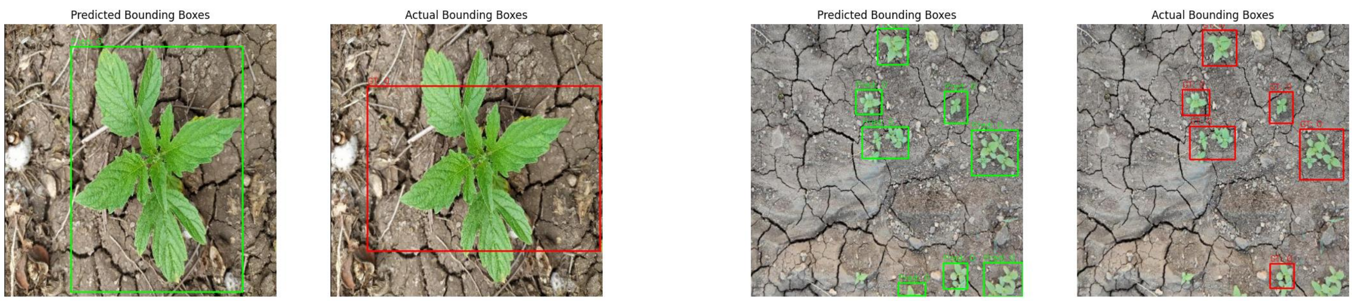
Table 1: Model Performance Comparison



6 Challenges

One of the significant challenges encountered during evaluation was the discrepancy between the ground truth labels and the model's predictions. Our model demonstrated superior detection capabilities, accurately identifying weeds that were either partially labeled or completely missing in the provided ground truth annotations. As a result:

- The model's precision and recall appeared lower due to mismatches with ground truth labels.
- The mAP metric was adversely affected, as it penalized detections that were not present in the original annotations.
- Despite the lower metric scores, qualitative analysis showed that the model provided better weed localization and detection compared to the labeled dataset.



(a) (b)

Figure 1: Discrepancy in predictions and ground truth annotations

This discrepancy highlights the limitations of the original labeling and suggests that our model could be leveraged to refine and improve annotation quality in future datasets.