Semi-Supervised Weed Detection Challenge

I. INTRODUCTION

Accurate and efficient weed detection is crucial for automating agricultural tasks such as targeted weed removal, leading to increased productivity and reduced manual labor. However, training robust object detection models typically requires large amounts of meticulously labeled data, which is expensive and time-consuming to acquire.

This project addresses this limitation by implementing semi-supervised learning (SSL) to leverage a small labeled dataset and a larger unlabeled dataset. Our goal is to train an effective weed detection model capable of accurately identifying and localizing weeds within agricultural images while minimizing the reliance on extensive labeled data.

II. IMPLEMENTED TECHNIQUE

A. Model training using labeled data:

We used *YOLO11n.pt* model, and train this model with the labeled data. A baseline model has been generated.

B. Pseudo-Labeling:

We used that baseline model to generate pseudo-labels for the unlabeled dataset. These pseudo-labeled images were incorporated into training in an iterative manner.

III. TRAINING METHODOLOGY

A. Dataset:

- Labeled: 200 images with sesame crops and weeds.
- Unlabeled: 1000 similar images without labels.
- Test Set: 50 images with ground-truth annotations.

B. Architecture

We used *YOLO11* object detection model

C. Data Preprocessing:

First we preprocess the labeled data, and made the total labeled dataset size double.

- Random Cropping and Horizontal Flipping: To introduce spatial variability.
- CutMix and MixUp: To blend images and improve classification robustness.
- Color Jittereing: o enhance the effectiveness of consistency regularization.

D. Initial Training:

Initial Training: The model was first trained on labeled data using cross-entropy and localization loss.

```
Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|##########| 3/3 [00:03<00:00,  1.04s/it]
  all         40         82      0.818      0.681      0.751       0.42
 weed         18         54      0.761      0.611      0.662      0.334
 crop         22         28      0.876       0.75      0.839      0.506
```

Fig. 1. Score for baseline model

```
Class     Images  Instances      Box(P          R      mAP50  mAP50-95):  50%|#####     | 2/4 [00:02<00:02,  1.21s/it]
Class     Images  Instances      Box(P          R      mAP50  mAP50-95):  75%|#######5  | 3/4 [00:03<00:01,  1.19s/it]
Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|##########| 4/4 [00:03<00:00,  1.23it/s]
Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|##########| 4/4 [00:03<00:00,  1.04it/s]
  all         50         74      0.909      0.845      0.907      0.573
 weed         24         42       0.95      0.908      0.957      0.639
 crop         26         32      0.867      0.781      0.856      0.507
```

Fig. 2. Scores after retraining with pseudo-labels

E. Challenges Faced:

Here the problem was that the precision and recall value of the model was low, means the model is predicting too many positive instances incorrectly, and the model is failing to identify many actual positive cases.

F. Pseudo-Labeling:

Unlabeled images with high-confidence(0.80) predictions were assigned pseudo-labels and incorporated into training.

G. Retrain:

Using that data with pseudo labels with some argumentations, we retrained our basline model.

H. Challenges Faced:

Now the main challenge was to improve mAP50-95 value. Because our was detecting the weed and crop accurately but sometimes the bounding box area becomes larger. Also sometimes it is showing one box for more than two weed or crop.

I. Re-Labeled the Unlabeled data:

Now our model is almost accurate in detection of weed or crop. so we used our model to generate labels of the unlabeled data once again.

J. Re-Train:

As there was a problem with the bounding box area, we scaled up the images for better resolution, and also added some data argumentation as mentioned before. Then using that large dataset we retrained our model again.

```
Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|##########| 4/4 [00:03<00:00,  1.03it/s]
  all         50         74      0.964      0.892      0.977      0.664
 weed         24         42      0.928      0.952      0.982      0.696
 crop         26         32          1      0.831      0.972      0.632
```

Fig. 3. Score after Final Training

IV. RESULT:

Performance was evaluated using the metric: 0.5 * (F1-Score) + 0.5 * (mAP@[.5:.95])

- Baseline (Supervised Only, 200 Labeled Images): 0.582
- After Pseudo-Labeling: 0.725
- Final Model: 0.795

By incorporating unlabeled data effectively, our semi-supervised models demonstrated substantial improvements over the baseline.

V. CONCLUSION:

This report provides a concise overview of our semi-supervised weed detection approach, methodology, challenges, and key takeaways.