# Semi-Supervised Weed Detection using YOLOv8

Leveraging Pseudo-Labeling for Improved Performance

- INTRODUCTION
- •- Weed detection in agriculture is critical for yield optimization.
- •- Fully labeled datasets are expensive and time-consuming to create.
- •- We use a semi-supervised approach combining labeled and unlabeled data.
  - •- Our method involves pseudo-labeling for better model performance.







#### DATASET AND PREPROCESSING

## Let's begin by examining the dataset given and how we process it

- Initial labeled dataset: 200 images
- Later augmented to 600
- Unlabeled dataset: 1000 images.
- Data augmentation using Albumentations.
- Flips, rotations, brightness contrast adjustments.
- Preprocessing for YOLOv8 training.

#### BASELINE YOLOV8 MODEL

- Used augmentation to improve generalization.
- •- Trained on 600 labelled images.
- •- Achieved initial evaluation score of 0.73.
- Next step: Leverage unlabelled data with semi-supervised learning.

#### PSEUDO-LABELING STRATEGY

**Predictions with confidence > Trained YOLOvs8 model on** 0.80 are added as pseudo-Trained YOLOvm8 model on the new dataset and again labels and combined with tested on the unlabelled data. 600 pre-processed images. the previous 600 images. **Predictions with confidence > Model is tested on the test** 0.80 are added as pseudo-Model is retrained on the new labels and combined with data and we got accuracy as and final training dataset. 73.60%. the previous images.

#### **EVALUATION AND PERFORMANCE**

- •- Performance metrics:
- Mean Average Precision (mAP)
- Precision and Recall
- •- Metric for evaluation: 0.5 \* (F1-Score) + 0.5 \* (mAP@[.5:.95])
- •- Iterative improvement using pseudo-labelling.

### CONCLUSION AND FUTURE WORK

- Semi-supervised learning effectively improves weed detection.
- Pseudo-labeling and FixMatch help utilize unlabeled data.

#### **Future work:**

- Fine-tuning confidence thresholds.
- Exploring more augmentation strategies.
- Deploying model in real-world settings.



