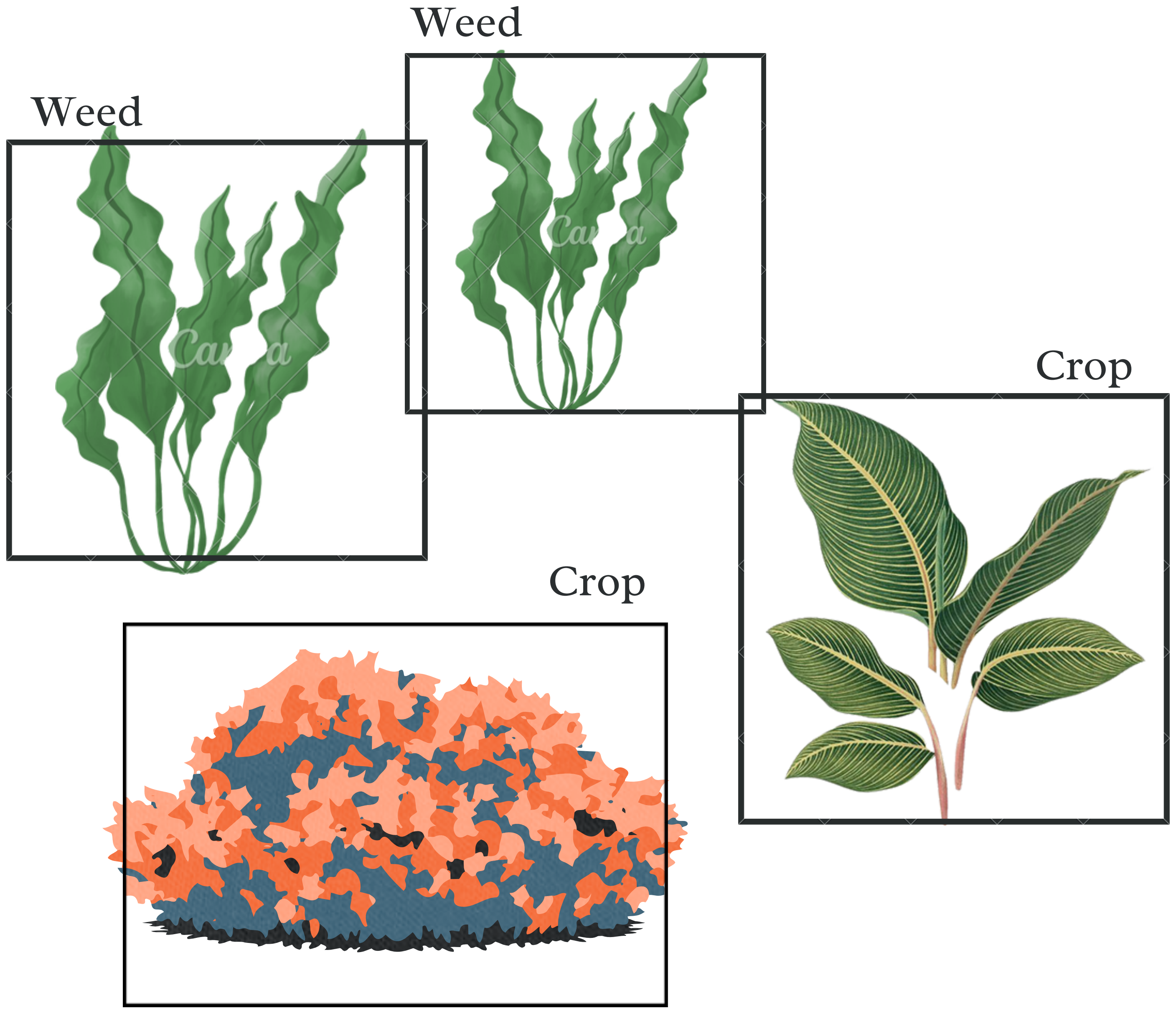
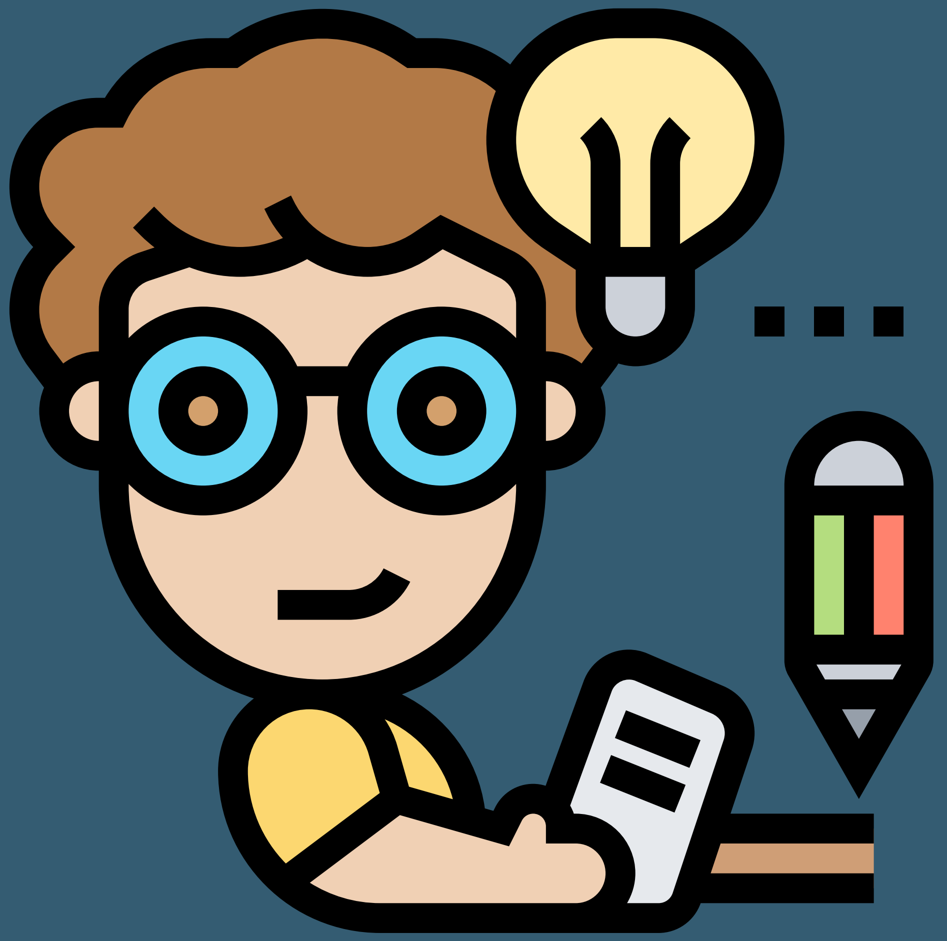


SEMI-SUPERVISED WEED DETECTION

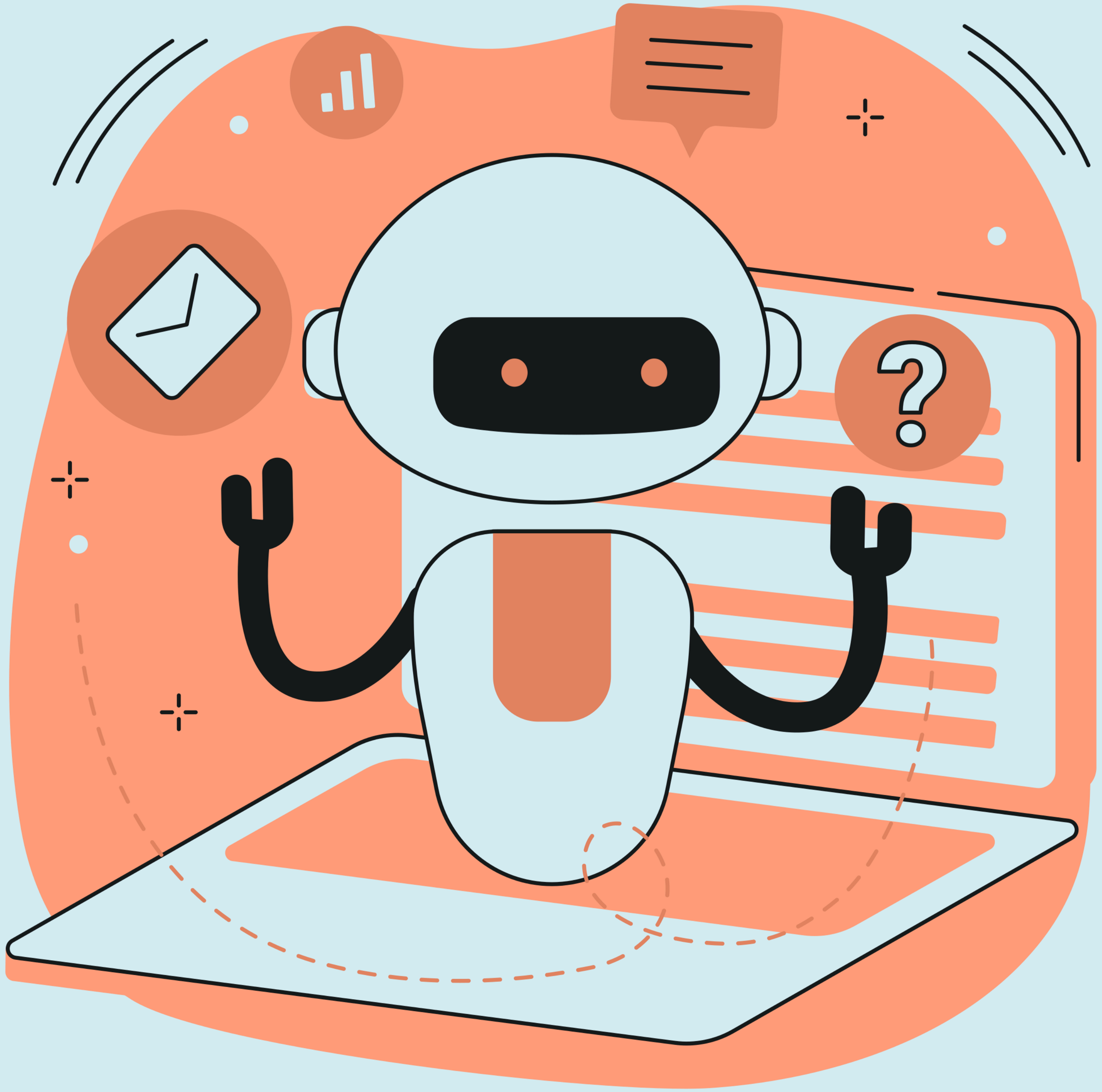
HOSTEL 76

Contents



Overview

In agricultural fields, efficient weed detection is essential to optimize crop yields and minimize the use of herbicides. However, the challenge lies in the limited availability of labeled data for training machine learning models. To address this, this project develops a robust weed detection model by leveraging semi-supervised learning techniques, specifically combining YOLO with methods like consistency regularization, pseudo labeling, and the Mean Teacher model. This approach enables the model to effectively utilize both labeled and unlabeled data, improving its detection accuracy and robustness over time.



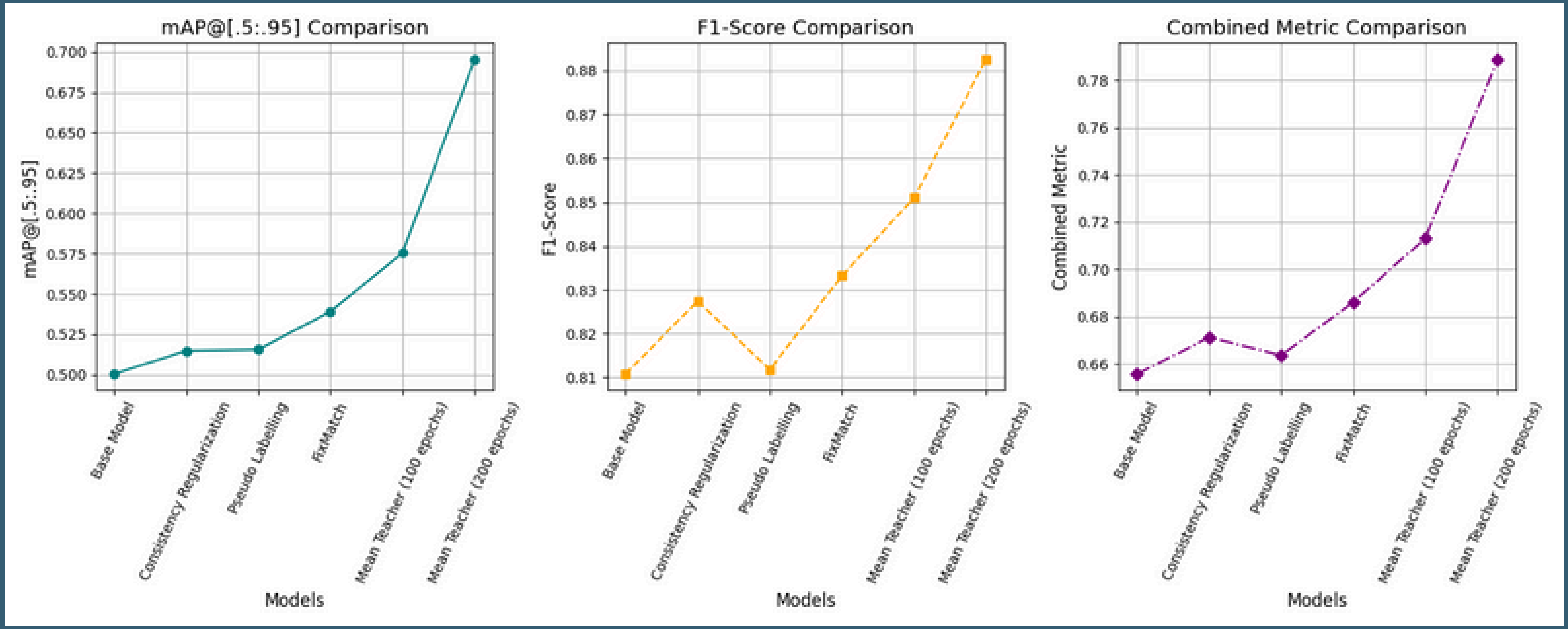
Data Preparation

Effective data preparation is key to ensuring the success of any machine learning model, especially when dealing with limited labeled data. In this project, we focused on transforming and augmenting the dataset to enhance its diversity and ensure it was suitable for YOLO-based training. Key steps included applying rotations and horizontal flips to augment labeled data and adjusting bounding boxes accordingly. The dataset was then structured into training, validation, and unlabeled sets, allowing for a seamless integration of semi-supervised learning techniques. Additionally, the dataset was formatted to comply with YOLO's requirements, ensuring compatibility and efficient training.

Training Methodology

The training methodology combines both supervised and semi-supervised learning techniques to optimize the performance of the weed detection model. Initially, the model was trained using labeled data with YOLO11m, leveraging standard configurations such as a batch size of 16 and a learning rate of 5e-5. To further enhance model performance, consistency regularization, pseudo labeling, and the Fix-Match algorithm were employed, enabling the model to learn from unlabeled data. The Mean Teacher model was also used to guide learning through an exponential moving average, improving the model's robustness. Throughout the training process, weak and strong augmentations were applied to ensure stability and consistency in predictions, resulting in a progressively improved model.

Model Performance

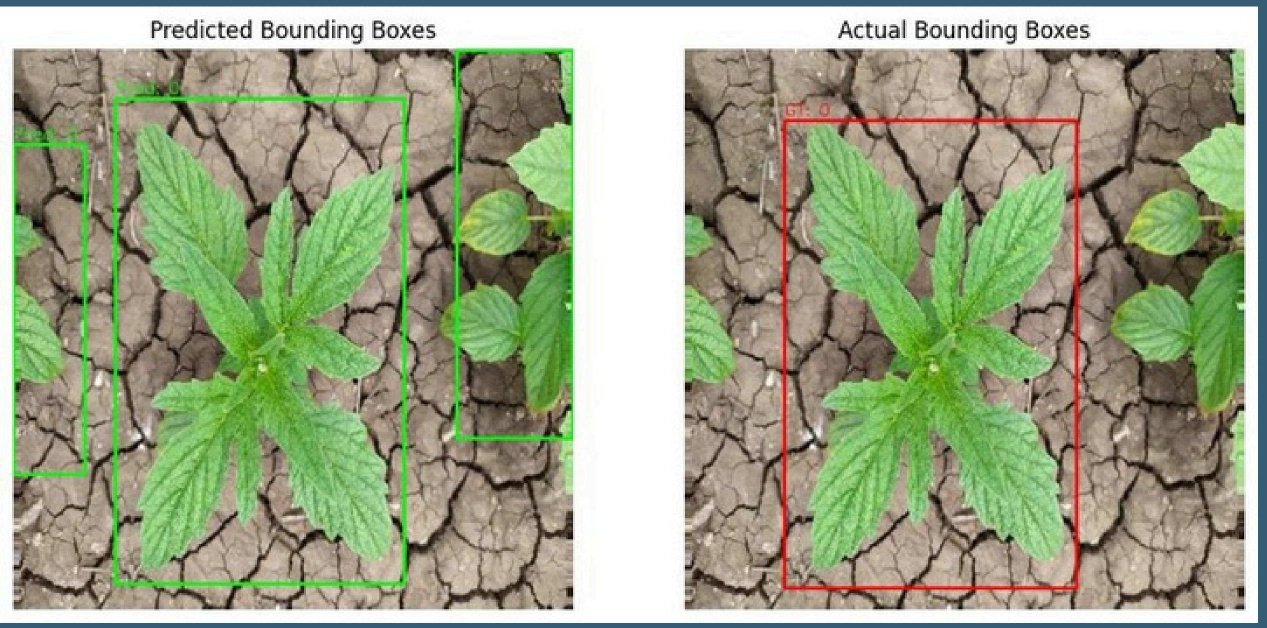


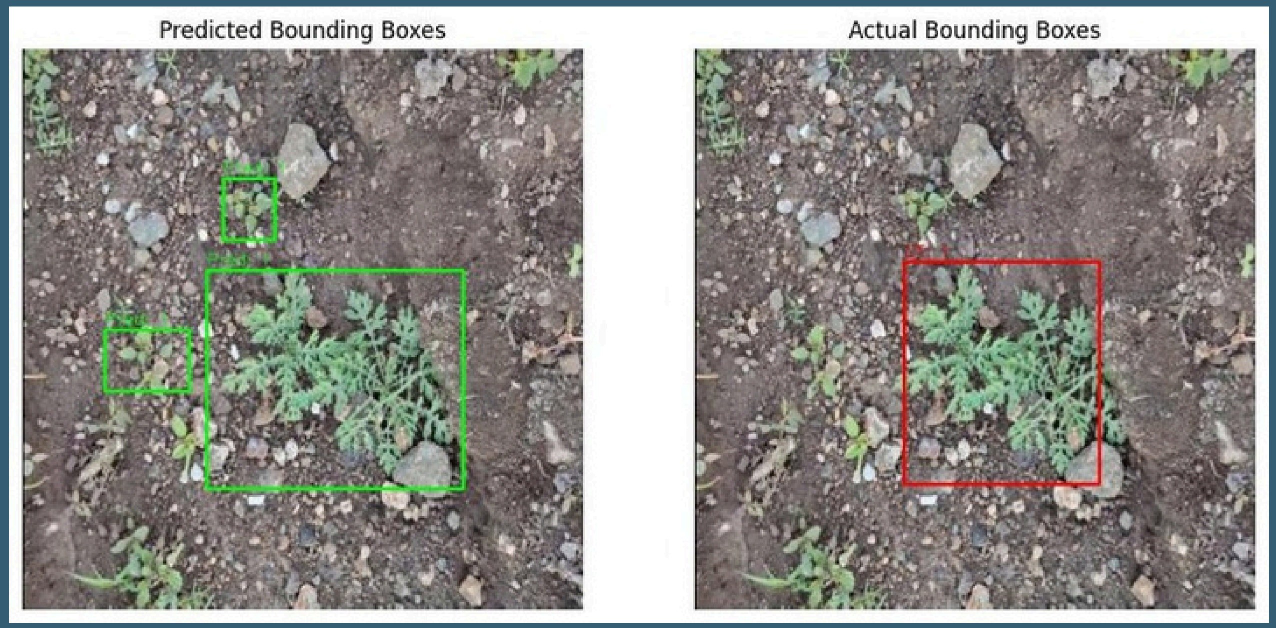
Results

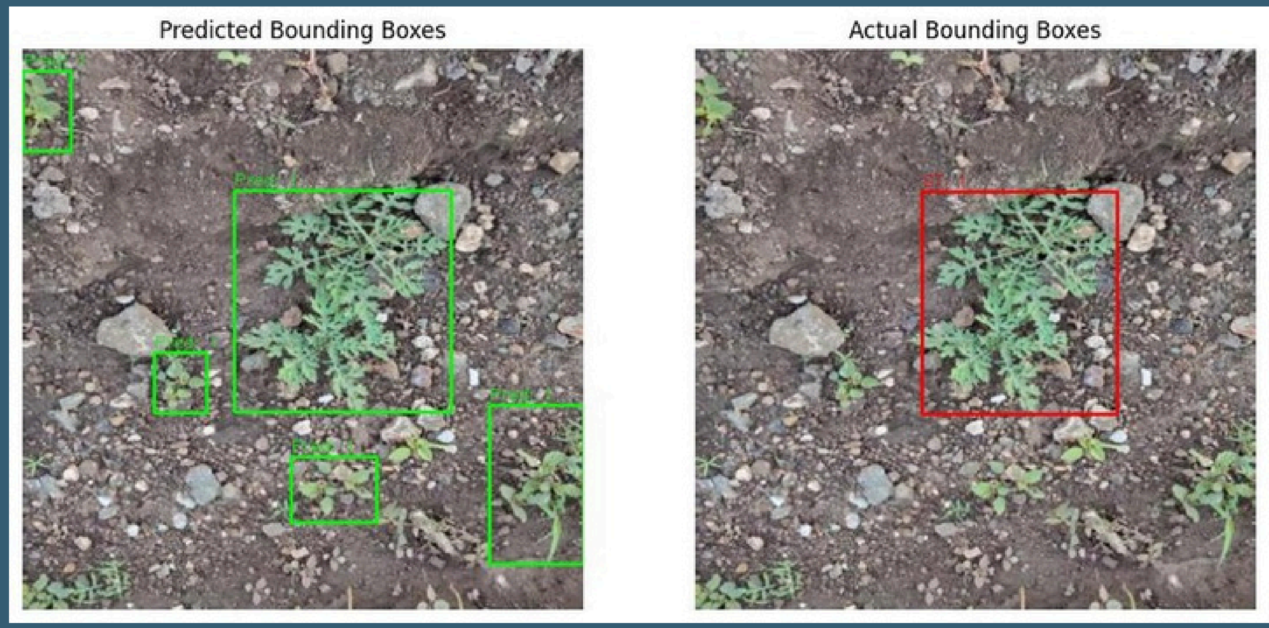
Model	*Precision*	*Recall*	*mAP50*	*mAP50-95*	*Fitness*	*F1 Score*	*Combined Metric*
Base Model	0.8619	0.7655	0.8455	0.5005	0.5350	0.8108	0.6557
Consistency Regularization	0.8078	0.8481	0.8409	0.5150	0.5476	0.8275	0.6712
Pseudo Labeling	0.8027	0.8212	0.8408	0.5157	0.5482	0.8118	0.6637
FixMatch	0.8681	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

Challenges faced

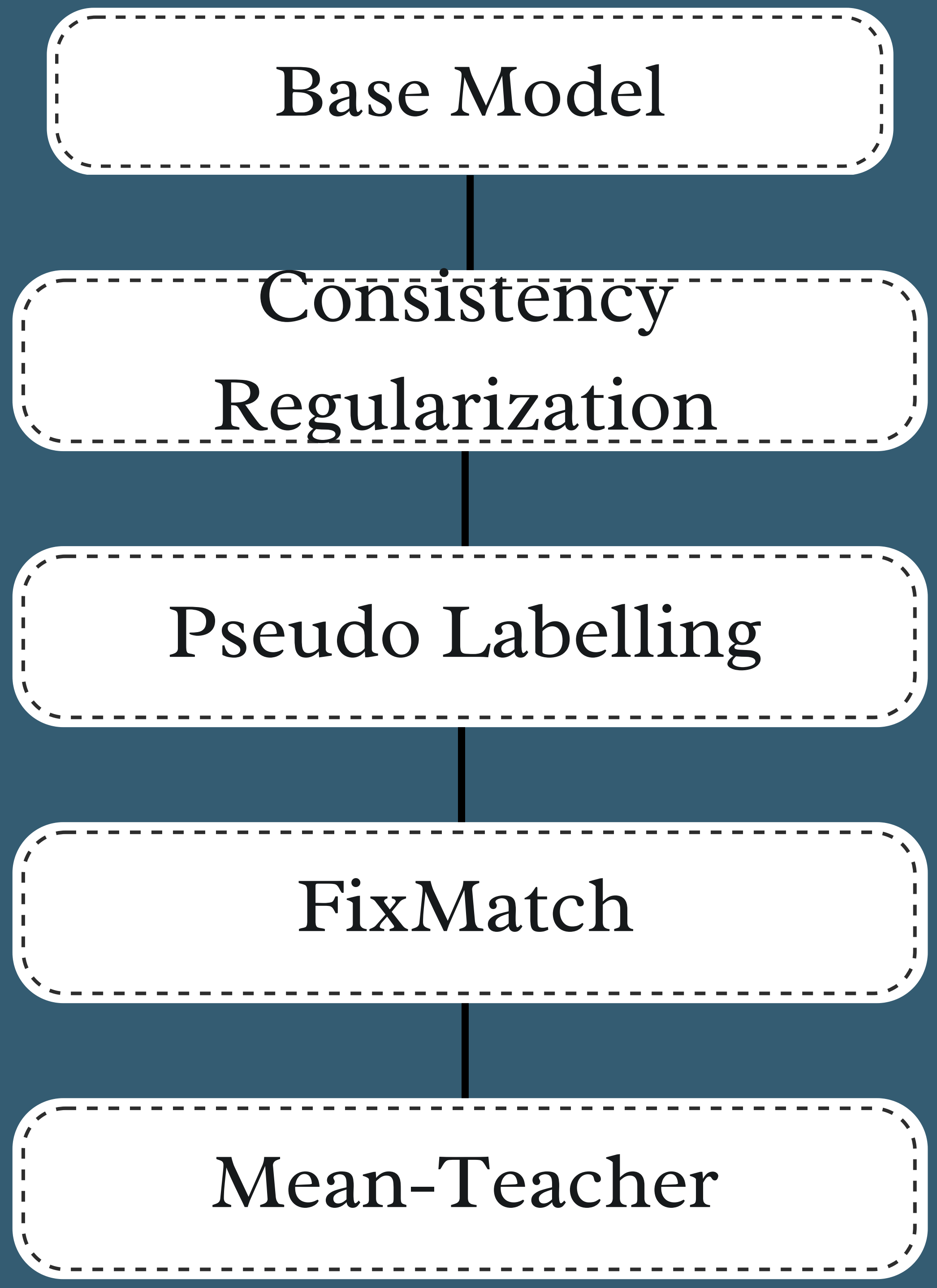
One of the primary challenges encountered during the project was the mismatch between the ground truth labels and the model’s predictions. The model often detected weeds that were either partially labeled or completely absent from the provided annotations. This discrepancy led to lower precision and recall scores, as the model's predictions did not always align with the ground truth. Furthermore, the mAP metric was negatively impacted due to penalties for these mismatches. However, qualitative analysis revealed that the model excelled in accurately localizing and detecting weeds compared to the labeled dataset, suggesting that the model could potentially improve the quality of annotations in future datasets.





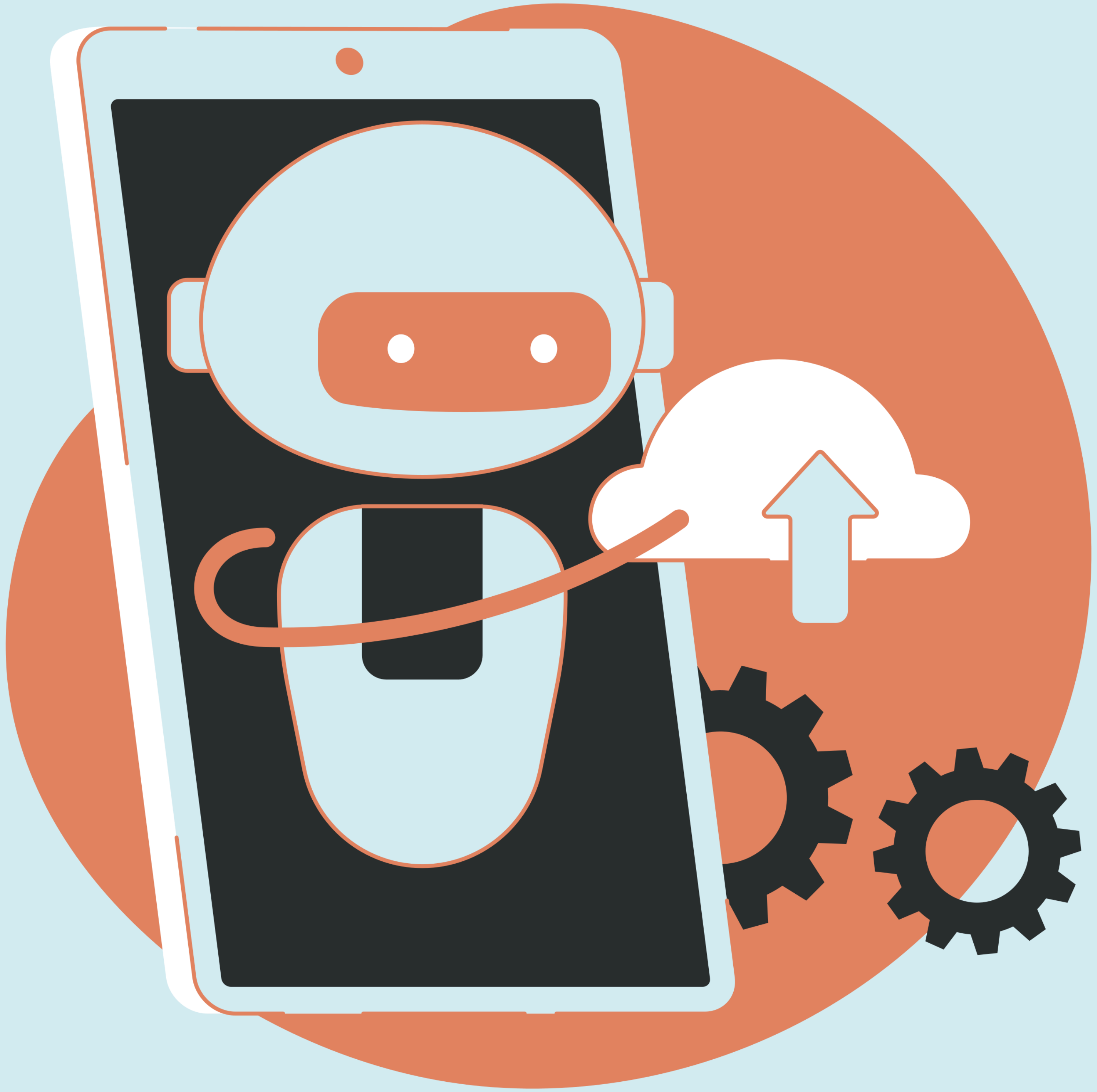


Pipeline


Base Model
Consistency Regularization
Pseudo Labelling
FixMatch
Mean-Teacher

Future Improvements

1. Curriculum Learning
2. Ensemble Learning
3. Quantization and Pruning
4. Explainable AI
5. Model Deployment and Real-Time Detection



References

1 YOLO Ref.- https://arxiv.org/abs/1506.02640

2 Fixmatch Ref.- https://arxiv.org/abs/2001.07685

3 Mean Tr. Ref.- https://arxiv.org/abs/1703.01780

THANK YOU FOR LISTENING!