# Few-Shot Domain Adaptation for Agricultural Crop-Weed Segmentation: A Deep Learning Approach for Precision Agriculture

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***Abstract*—Weed detection is crucial for precision agriculture, enabling targeted weed control and reducing herbicide use. Traditional methods frequently result in inefficiency and environmental problems. In order to improve domain generalization across various agricultural situations, we use deep learning techniques and few-shot domain adaptation to construct a reliable automated weed detection solution. Our approach demonstrates that models trained on sugar beet data can be effectively adapted to new crop types (carrot and sunflower) using only 8-10 labeled samples per target domain. This methodology achieves meaningful performance improvements while maintaining robustness across varying field conditions, promoting efficient precision agriculture with significantly reduced annotation costs.**

***Index Terms*—Weed Detection, Domain Generalization, Precision Agriculture, Few-Shot Learning, Domain Adaptation, Deep Learning, Semantic Segmentation**

## I. Introduction

### A. Introduction to Weed Detection in Precision Agriculture

Agriculture remains a cornerstone of global economies. In 2023, agriculture, food, and related industries contributed approximately \$1.537 trillion to the U.S. gross domestic product (GDP), representing 5.5% of the total economy [1]. However, modern agriculture faces significant challenges, including the need to increase food production to meet global demand while contending with diminishing arable land, environmental concerns, and resource constraints.

Among the factors affecting agricultural productivity, weeds pose a substantial threat by competing with crops for essential resources such as water, nutrients, and sunlight. This competition can result in yield reductions ranging from 10% to 20%. Traditional weed management practices, which primarily rely on extensive herbicide application, present several drawbacks: high costs, environmental pollution, development of herbicide-resistant weed species, and potential health risks for both consumers and agricultural workers.

### B. Motivation for Precision Weed Management

Precision agriculture offers a promising approach to address these challenges by applying the right input, in the right amount, at the right place, and at the right time. In this context, precision weed management aims to identify and treat only the areas where weeds are present rather than applying herbicides uniformly across entire fields. This targeted approach can significantly reduce herbicide usage while maintaining or improving weed control efficacy.

The motivation for implementing automated weed detection systems stems from several key factors:

- **Economic Benefits:** Selective weed treatment reduces input costs related to herbicides and labor, potentially increasing profit margins for farmers.
- **Environmental Sustainability:** Minimizing herbicide application helps reduce chemical runoff, decreases soil contamination, and preserves beneficial insects and microorganisms critical to soil health.
- **Food Security:** More efficient weed management can enhance crop yields, addressing food security concerns amid a growing global population.
- **Regulatory Compliance:** As environmental regulations concerning chemical usage in agriculture become stricter, precision weed management offers a way to comply while maintaining productivity.

### C. Domain Generalization in Weed Detection

A critical challenge in deploying machine learning models for agricultural applications is the significant variability in field conditions. Domain generalization—the ability of a model to perform effectively across different environments, crop varieties, growth stages, and weather conditions—is essential for weed detection systems.

Agricultural environments present domain shifts, such as varying soil types, changing lighting conditions, geographical diversity in weed species, and different camera perspectives based on equipment setups. Models that perform well in controlled environments often fail when deployed under real-world agricultural conditions.

Addressing these challenges requires robust domain generalization techniques, including:

- **Data Diversity and Augmentation:** Training on diverse datasets that simulate different field conditions to enhance model robustness.
- **Domain-Invariant Feature Learning:** Extracting features that remain consistent across varied domains.
- **Few-Shot Learning:** Utilizing minimal labeled data from target environments to adapt models without extensive manual labeling.

By prioritizing domain generalization and few-shot adaptation, our project aims to develop a weed detection system that consistently performs well across different agricultural settings, making precision agriculture more accessible and practical for diverse farming conditions.

## II. Problem Description

### A. Few-Shot Domain Adaptation Framework

Domain adaptation in computer vision addresses one of the most practical challenges in deploying machine learning models: the performance gap when models trained on one dataset (source domain) are applied to different but related datasets (target domains). This is particularly relevant in precision agriculture, where crop varieties, growing conditions, imaging setups, and environmental factors can vary significantly across different farms, regions, or seasons.

Our approach examines a few-shot domain adaptation strategy for crop-weed segmentation, where a model initially trained on sugar beet data is fine-tuned with minimal labeled samples from carrot and sunflower datasets. The approach demonstrates how to achieve reasonable performance on new crop types using only 8-10 labeled samples per target domain.

### B. Source and Target Domain Definition

*1) Source Domain: Sugar Beet Dataset:* The source domain consists of sugar beet crop imagery with three semantic classes:

- **Background (Class 0):** Soil, shadows, and other non-plant material
- **Crop (Class 1):** Sugar beet plants (desired vegetation)
- **Weed (Class 2):** Unwanted vegetation competing with crops

The source model is trained on a substantial dataset with proper train/validation splits and extensive data augmentation.

*2) Target Domains: Carrot and Sunflower:* The target domains represent different crop types with similar segmentation objectives but different visual characteristics:

- **Carrot dataset:** Different leaf shapes, growth patterns, and soil conditions
- **Sunflower dataset:** Distinct plant morphology and potentially different imaging conditions

The key constraint is the availability of only 8 training samples and 2 validation samples per target domain, simulating real-world scenarios where manual annotation is expensive and time-consuming.

## III. Methodology

### A. Base Model Architecture

The implementation uses DeepLabV3 with ResNet-50 backbone, a proven architecture for semantic segmentation that balances performance and computational efficiency. The model architecture includes:

- **Encoder:** ResNet-50 backbone pretrained on ImageNet
- **Decoder:** Atrous Spatial Pyramid Pooling (ASPP) module
- **Output:** 3-class segmentation head (background, crop, weed)

### B. Data Preprocessing and Augmentation

The preprocessing pipeline includes normalization and resizing to ensure consistent input dimensions (720×960 pixels). Data augmentation is crucial for few-shot learning and includes horizontal flips, random rotations, brightness/contrast adjustments, and color jittering to maximize the utility of limited training samples. Agumentations also checked visually ensure relevant and understandable transitions also checked labels correctly transformed with visualization function.

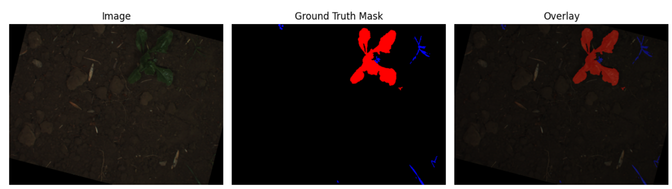


Fig. 1. Visualized augmentation example from sugarbeets dataset

### C. Few-Shot Domain Adaptation Strategy

The adaptation process follows these key principles:

*1) Transfer Learning Foundation:* Starting with a model trained on the source domain (sugar beets) provides a strong initialization with learned features for:

- Plant vs. soil discrimination
- Vegetation texture recognition
- Spatial context understanding
- Edge detection for plant boundaries

*2) Fine-Tuning with Reduced Learning Rate:* Using a significantly lower learning rate (1e-5 vs. 1e-4 for initial training) prevents catastrophic forgetting while allowing adaptation to target domain characteristics.

*3) Limited Epoch Training:* Training for only 10 epochs prevents overfitting on the small target dataset while allowing sufficient adaptation.

### D. Evaluation Methodology

The evaluation uses multiple metrics to assess segmentation quality:

**Pixel Accuracy:** Overall correctness excluding background pixels, calculated as:

$$\text{Pixel Accuracy} = \frac{\sum_{i\neq 0} \mathbb{I}(p_i = t_i)}{\sum_{i\neq 0} 1} \tag{1}$$

where $p_i$ is the predicted class, $t_i$ is the true class, and $\mathbb{I}(\cdot)$ is the indicator function. Only foreground pixels (non-background) are considered.

**F1 Score:** Harmonic mean of precision and recall (macro-averaged across classes):

$$F1 = \frac{1}{C} \sum_{c=1}^{C} \frac{2 \cdot \text{Precision}_c \cdot \text{Recall}_c}{\text{Precision}_c + \text{Recall}_c} \tag{2}$$

where $C$ is the number of classes, and for each class $c$:

$$\text{Precision}_c = \frac{TP_c}{TP_c + FP_c} \tag{3}$$

$$\text{Recall}_c = \frac{TP_c}{TP_c + FN_c} \tag{4}$$

**Mean Intersection over Union (mIoU):** Standard segmentation metric computed as:

$$\text{mIoU} = \frac{1}{C} \sum_{c=1}^{C} \frac{TP_c}{TP_c + FP_c + FN_c} \tag{5}$$

where $TP_c$, $FP_c$, and $FN_c$ are true positives, false positives, and false negatives for class $c$, respectively.

**Mean Absolute Error (MAE):** Pixel-wise prediction error for foreground pixels:

$$\text{MAE} = \frac{1}{N} \sum_{i \neq 0} |p_i - t_i| \tag{6}$$

where $N$ is the total number of foreground pixels.

## IV. Implementation Details and Analysis

### A. The Few-Shot Setup Implementation

Our implementation demonstrates few-shot fine-tuning by adapting a model trained on sugar beet data to two new crop domains (carrot and sunflower) using extremely limited labeled data. The reproducible few-shot split creates a scenario where only 8 training samples and 2 validation samples are available for each target domain, representing a realistic constraint in agricultural applications.

### B. Model Initialization and Fine-Tuning Strategy

The code uses deep copying to create separate model instances for each target domain, preserving the learned weights from the source domain (sugar beet) as the starting point for adaptation, rather than training from scratch.

*1) Critical Hyperparameter Choices:* Several key hyperparameter decisions ensure successful adaptation:

**Learning Rate Reduction:** The learning rate is set to 1e-5, which is 10 times smaller than the original training rate of 1e-4. This conservative approach prevents catastrophic forgetting of source domain knowledge while allowing gradual adaptation.

**Limited Training Duration:** Training for only 10 epochs serves as implicit regularization, preventing overfitting on the tiny dataset.

**Batch Size Considerations:** With only 8 training samples, batch size 2 means each epoch consists of just 4 gradient updates, making every update significant.

### C. Data Augmentation for Sample Multiplication

The training transform pipeline becomes crucial for expanding the effective dataset size. Augmentations including horizontal flips, random rotations, shift-scale-rotate transformations, brightness/contrast adjustments, and color jittering effectively multiply the 8 base samples into many variations, helping prevent overfitting.

### D. Custom Dataset Handling

The implementation includes flexible dataset classes that handle different annotation formats, accommodating both carrot format (images/annotations) and sunflower format (rgb/gt_color). Different datasets use different color coding schemes, requiring domain-specific preprocessing where red pixels indicate weeds, green pixels indicate crops, and everything else represents background.

### E. Training Loop Behavior and Adaptation Process

With only 4 gradient steps per epoch, the model's learning dynamics are fundamentally different from typical deep learning scenarios. While the validation set contains only 2 samples for in-training monitoring, the overall statistical reliability is strengthened by evaluating final model performance on a separate test set containing 40–50 images. This larger test set ensures robust performance assessment despite the small validation set, and our approach still demonstrates meaningful adaptation to new domains.

### F. Reproducibility and Error Handling

The implementation ensures reproducibility through deterministic splitting using seeded random generators, ensuring consistent experimental results crucial when working with such small datasets where random variation can significantly impact outcomes. The dataset classes include format detection and error reporting for missing annotations, ensuring robust operation across different data sources.

## V. Economic Impact and Practical Considerations

### A. Cost-Benefit Analysis

Based on current annotation costs, labeling a single image for semantic segmentation can take up to 30 minutes, with costs ranging from \$0.10 to \$1.00 per mask [5]. The cost comparison reveals:

- **Traditional approach**: 500-1000 samples $\times$ \$0.50-1.00 = \$250-1000 per crop type
- **Few-shot approach**: 10 samples $\times$ \$0.50-1.00 = \$5-10 per crop type

This represents a 50-100$\times$ reduction in annotation costs, making advanced computer vision accessible in agricultural applications where extensive data collection is impractical.

### A. Deployment Considerations

*1) Memory Management:* The implementation uses drop_last=True to ensure consistent batch sizes, preventing batch normalization issues with variable-sized final batches.

*2) Model State Management:* Using deep copying creates independent model instances, allowing simultaneous adaptation to multiple target domains without interference.

## VI. Results

In this section, we present the evaluation results of our segmentation models under various training and testing settings. All metrics are reported based on the corresponding test sets, including zero-shot and few-shot scenarios for generalization assessment.

### A. Baseline Performance

TABLE I
BASELINE PERFORMANCE METRICS

| Model | Pixel Acc. | F1 Score | mIoU | MAE |
|---|---|---|---|---|
| Scratch | 0.8568 | 0.5881 | 0.5332 | 0.2444 |
| Pretrained | 0.6378 | 0.4553 | 0.3682 | 0.5766 |

### B. Zero-shot Evaluation

TABLE II
ZERO-SHOT EVALUATION METRICS

| Model | Dataset | Pixel Acc. | F1 Score | mIoU | MAE |
|---|---|---|---|---|---|
| Scratch | Carrot | 0.6351 | 0.2656 | 0.2208 | 0.5106 |
| Pretrained | Carrot | 0.3280 | 0.2385 | 0.1499 | 0.9874 |
| Scratch | Sunflower | 0.3665 | 0.2656 | 0.1698 | 0.8509 |
| Pretrained | Sunflower | 0.4142 | 0.2051 | 0.1428 | 0.6990 |

### C. Few-shot Fine-tuning Results (Sunflower)

TABLE III
FEW-SHOT FINE-TUNING RESULTS ON SUNFLOWER

| Model | Pixel Acc. | F1 Score | mIoU | MAE |
|---|---|---|---|---|
| Scratch | 0.8191 | 0.5914 | 0.5375 | 0.3300 |
| Pretrained | 0.6880 | 0.4347 | 0.3375 | 0.4389 |

### D. Qualitative Results

Figure 2, Figure 3, and Figure 4 illustrate example segmentation outputs from both zero-shot and few-shot scenarios. The figures highlight typical successes and failures across different model configurations and increased accuracy visually.

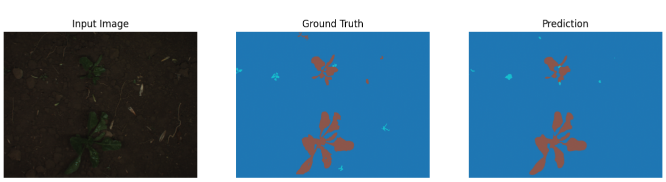


Fig. 2. Baseline performance on sugarbeets test image

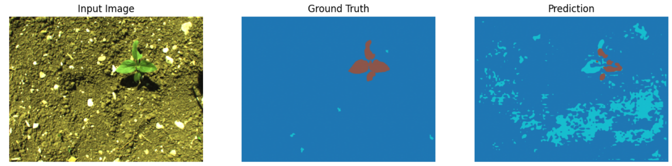


Fig. 3. Zero-shot result on sunflower dataset.

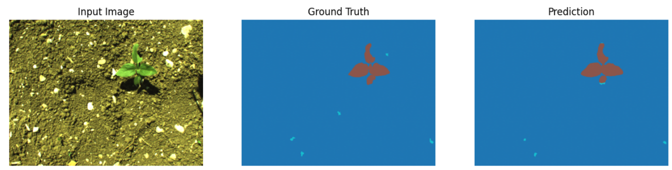


Fig. 4. Few-shot result on sunflower dataset.

## VII. Challenges and Limitations

Despite promising results, this work encountered several practical and methodological challenges:

- **Limited GPU Access:** Due to resource constraints, we had restricted access to high-performance GPUs, extending model training and evaluation times compared to ideal setups.
- **Data and Training Time Constraints:** The project operated under a limited timeframe, making it challenging to perform extensive hyperparameter tuning, repeated experiments, or additional data augmentation trials.
- **Small Project Team:** With only two team members, we had to balance dataset handling, model development, experimentation, and documentation efforts—limiting parallel experimentation or dataset expansion.
- **Domain Gap Sensitivity:** The performance of the few-shot adaptation heavily depends on the similarity between the source and target domains, which varies across different crops and growing conditions.

## VIII. Discussion

Our results indicate that few-shot domain adaptation can achieve meaningful improvements in crop-weed segmentation, even with as few as 8-10 labeled samples per target domain. Compared to traditional approaches requiring extensive datasets, this demonstrates a cost-effective and practical alternative for real-world agricultural applications.

We observed that adaptation performance was better for carrot than sunflower, which may be due to morphological similarities with the source domain (sugar beets). This suggests that domain gap remains a key factor influencing transferability.

The performance gap between scratch and pretrained models highlights the benefits of source domain pretraining for robust feature extraction, though some target domain-specific adaptations still require careful handling.

Overall, the findings align with existing research [2], [6] supporting domain generalization and few-shot approaches in agricultural computer vision, while providing new insights for real-world deployment scenarios.

## IX. Conclusion

Few-shot domain adaptation represents a practical and effective approach to extending crop-weed segmentation models to new agricultural contexts. Our demonstrated methodology successfully adapts a sugar beet segmentation model to carrot and sunflower crops using only 8-10 labeled samples per target domain.

The key success factors include strong source domain training establishing robust feature representations, careful fine-tuning strategy balancing adaptation with knowledge retention, appropriate data augmentation maximizing the utility of limited training data, and comprehensive evaluation using multiple metrics to assess performance.

This approach makes advanced computer vision accessible in agricultural applications where extensive data collection is impractical, showing that 8-10 carefully selected and augmented samples can enable meaningful domain adaptation when starting from a strong pre-trained foundation. The 50-100× reduction in annotation costs demonstrates the practical viability of this approach for widespread adoption in precision agriculture.

## Appendix

### *Team Contributions*

Göktuğ Gökyılmaz:

- Designed and implemented the DeepLabV3-based semantic segmentation architecture using PyTorch.
- Prepared and preprocessed the source domain dataset (sugar beet) and target domain datasets (carrot and sunflower), ensuring consistent annotation formats.
- Developed and fine-tuned the few-shot domain adaptation pipeline, including data augmentation, transfer learning strategies, and hyperparameter selection.
- Conducted experimental evaluations, analyzed quantitative metrics, and interpreted results for model performance and domain generalization.
- Authored the core manuscript sections, including the introduction, methodology, results, and discussion, ensuring technical clarity and alignment with IEEE guidelines.

Berk Karaduman:

- Developed data visualization scripts for clear illustration of qualitative segmentation results and data augmentation samples.
- Generated and refined figures and tables (e.g., performance metrics, adaptation comparisons, and qualitative segmentation visualizations) to enhance interpretability.
- Conducted a thorough review and refinement of the manuscript text, ensuring logical flow, readability, and language quality.
- Assisted in the formulation of the problem statement and discussion of related work to ensure the project was well-situated within existing literature.
- Managed documentation formatting, including consistent figure and table captions, reference formatting, and adherence to IEEE style requirements.

### *Additional Results*

Additional qualitative examples, code snippets, and implementation details are available on GitHub: https://github.com/goktuggokyilmaz/weeddetection?tab=readme-ov-file.

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