University of New Haven

TAGLIATELA COLLEGE OF ENGINEERING

MASTER OF SCIENCE IN DATA SCIENCE

Deep Learning Final Project Presentation

[Working Link]

Leaf Health Semantic Segmentation Using SegFormer

Meet the Team

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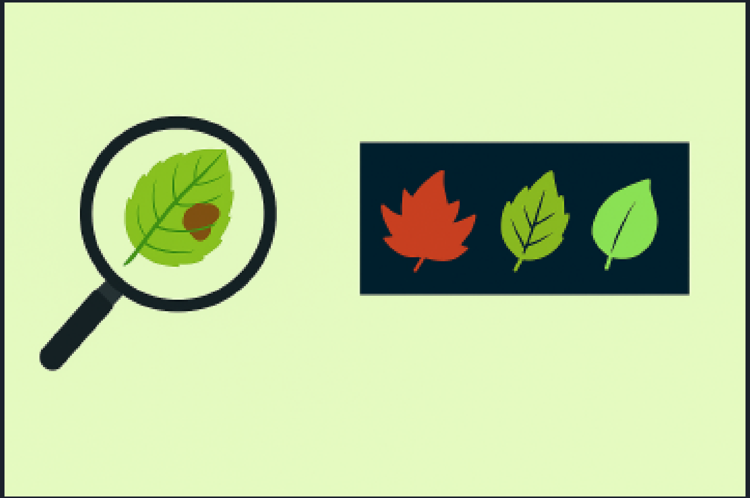
Introduction

- Task Description: The goal is to perform semantic segmentation of leaf regions into background, healthy leaf and dry leaf
- Target Object: Pixel-level classification of leaf health to support plant disease detection and agricultural automation.
- Why This Task Matters?
  - Manual inspection is slow and unreliable.
  - Automated segmentation helps monitor plant stress early.
  - Applicable in smart farming and environmental monitoring.



Dataset Overview

Collected 200 real leaf images using mobile phone camera

Each image has a manually created pixel level mask

Classes:

1. 0 – background
2. 1 – Healthy Leaf
3. 2 – Dry Leaf

Masks created using CVAT

Resolution standardized to 512x512

Healthy Leaf

Dry Leaf

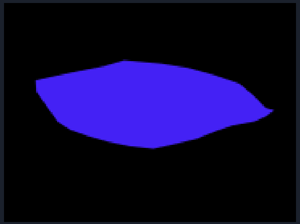
Dataset Details

- Task
    - Multi-class semantic segmentation
    - Predict health category for each pixel
- Dataset Link: [Dataset Link]
- Number of Samples
    - Total Images: ~200
    - Train: 80%
    - Validation: 10%
    - Test: 10%
- Image Size: 512×512 (after preprocessing)
- Normalization
    - Mean = (0.485, 0.456, 0.406)
    - Std = (0.229, 0.224, 0.225)
- Data Augmentation: Affine transforms, random brightness/contrast, grid distortion, elastic transform, noise + motion blur, horizontal & vertical flips and coarse dropout

Dataset Annotations

Annotation Structure (1 example)

```
{
  "image": "161.png",
  "mask": "161.png",
  "classes": {
      "0": "background",
      "1": "healthy_leaf",
      "2": "dry_leaf"
  }
}
```

Leaf No	Normal Image	Masked Image
10		
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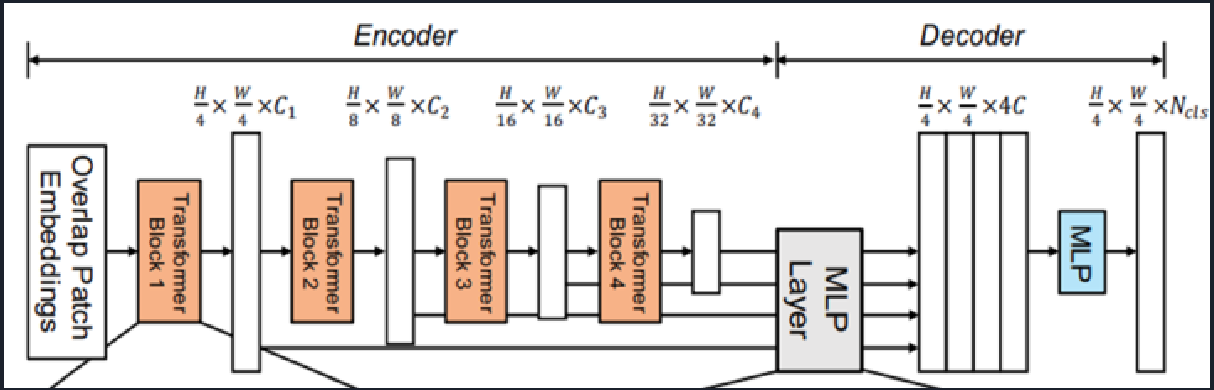
Methods (Overview)

- Model Used: SegFormer-B0
- Approach:
  - Use pretrained SegFormer encoder (MiT) from ADE20K
  - Replace segmentation head with 3-class output
  - Finetune using your leaf dataset
  - Improve performance with augmentation + Dice Loss
- Training Strategy:
  - CE finetuning → evaluate
  - CE + Dice finetuning → compare
  - Report both qualitative & quantitative results

Model Architecture

Base Neural Network: SegFormer-B0	Modifications to Adapt to this Task
• Overlapping Patch Embedding • 4-stage MiT Transformer Encoder • Multi-scale features (H/4 → H/32) • Lightweight MLP Decoder for segmentation • Final upsampling to full resolution	• Changed head to output 3 classes • Applied strong augmentations • Introduced Dice Loss to handle class imbalance • Tuned optimizer and LR via random search



Loss Functions

Training Objective Functions

- Cross Entropy Loss
    - Standard multi-class segmentation loss
- Dice Loss (Recent Technique)
    - Improves class imbalance handling
    - Enhances boundary segmentation
- Combined Loss = 0.5 CE + 0.5 Dice

Experiments

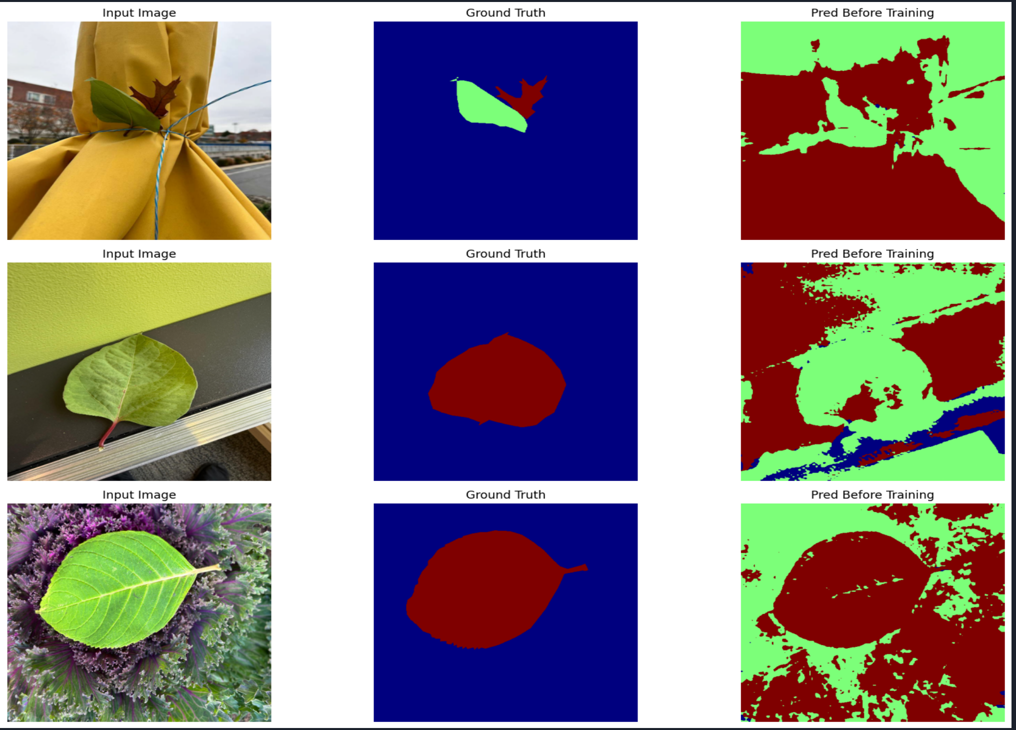
Experiment Pipeline

- Baseline inference using pretrained weights
- CE finetuning for 10 epochs
- CE evaluation (IoU, confusion matrix, samples)
- CE + Dice finetuning
- Comparison of improvements
- Metrics Used

Pixel Accuracy

- Mean IoU
- Confusion Matrix
- Qualitative visualizations

Qualitative Results Before Training



Optimization & Hyperparameter Tuning

Optimizers Tried: AdamW, SGD

Best Optimizer: AdamW

Hyperparameters Tuned

- Learning Rate: $[5e^{-5} \rightarrow 5e^{-4}]$
- Batch Size: $[4, 8, 16]$
- Weight Decay: $[0.0, 0.05]$

Tuning Strategy

- Random Search over 20 combinations
- Evaluate based on validation IoU

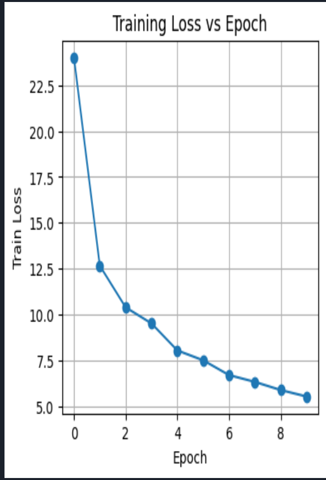
Best Parameters Found

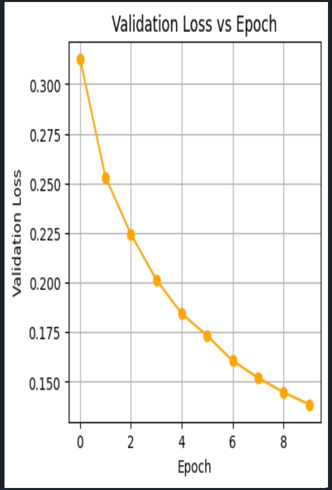
- LR = 1e-4
- Batch = 8
- Weight Decay = 0.05
- Optimizer = AdamW

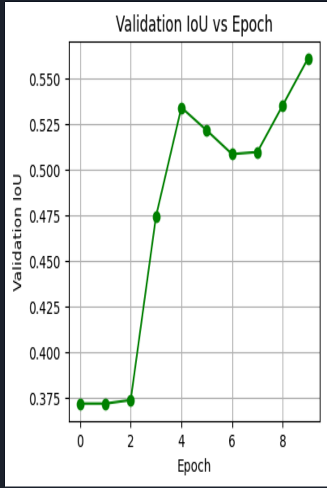
Finetuning Results (CE)

Experiment Setup
- CE-only finetuning
- 10 epochs
- Batch size 8
- AdamW optimizer

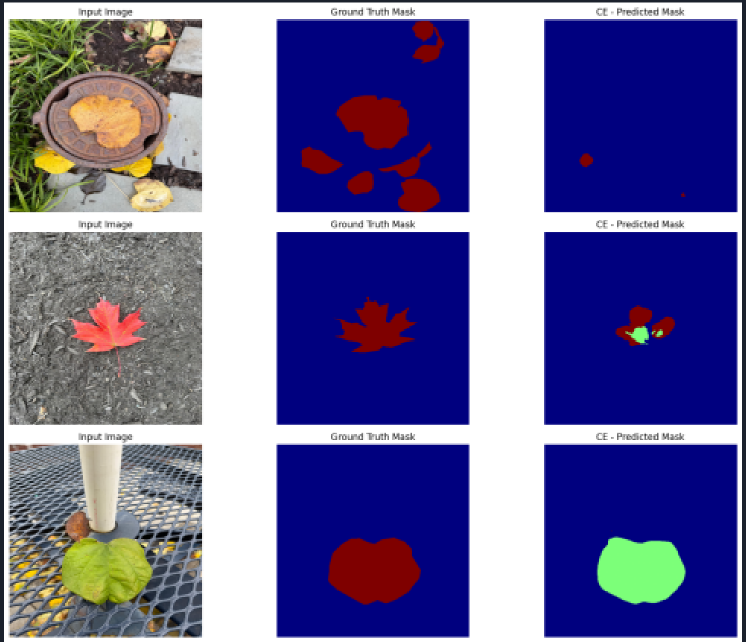
Quantitative Results
- Val IoU ≈ 0.83
- Good segmentation of healthy & dry leaf
- Strong generalization

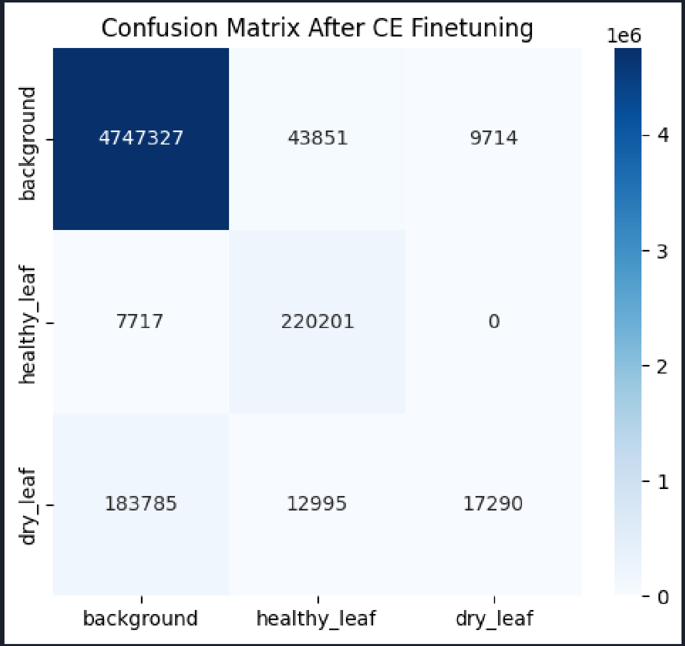






Results After Training (CE)





Transfer Learning vs Pretrained Model

Pretrained (Before Training)

- Incorrect segmentation
- High confusion with background
- Fails to separate healthy/dry leaf regions

After Fine-tuning

- Clear boundaries
- Accurate leaf region segmentation
- Strong detection of dry leaf patches

Conclusion:

- Transfer learning dramatically improves performance.

Dice Loss

What is Dice Loss?

- Measures the overlap between predicted and true regions.
- Designed for segmentation tasks with class imbalance.

Why Use It?

- Improves detection of small or rare regions (like dry leaf tissue).
- Produces sharper boundaries and better region consistency.

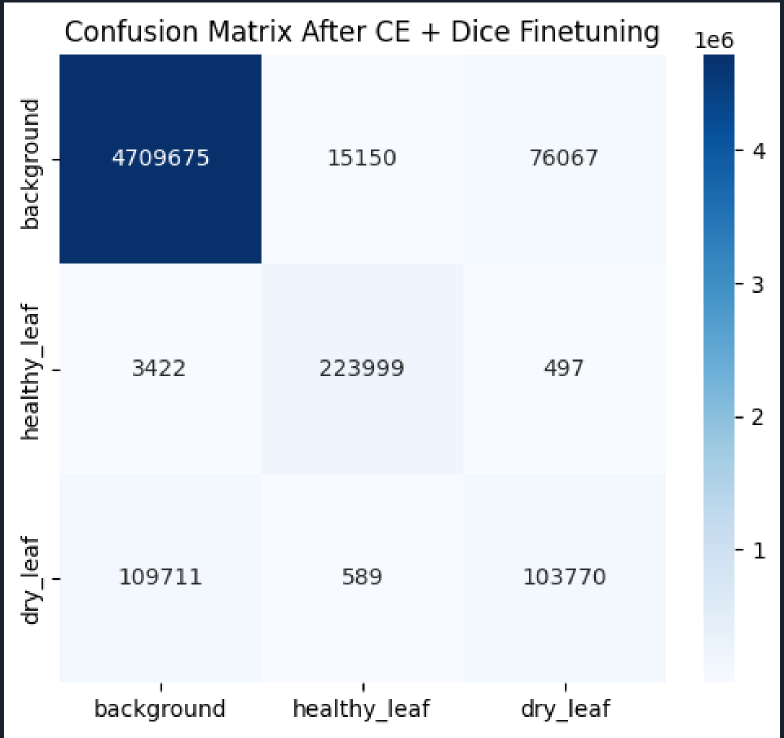
Formula:

$$Dice = 2TP / (2TP + FP + FN)$$

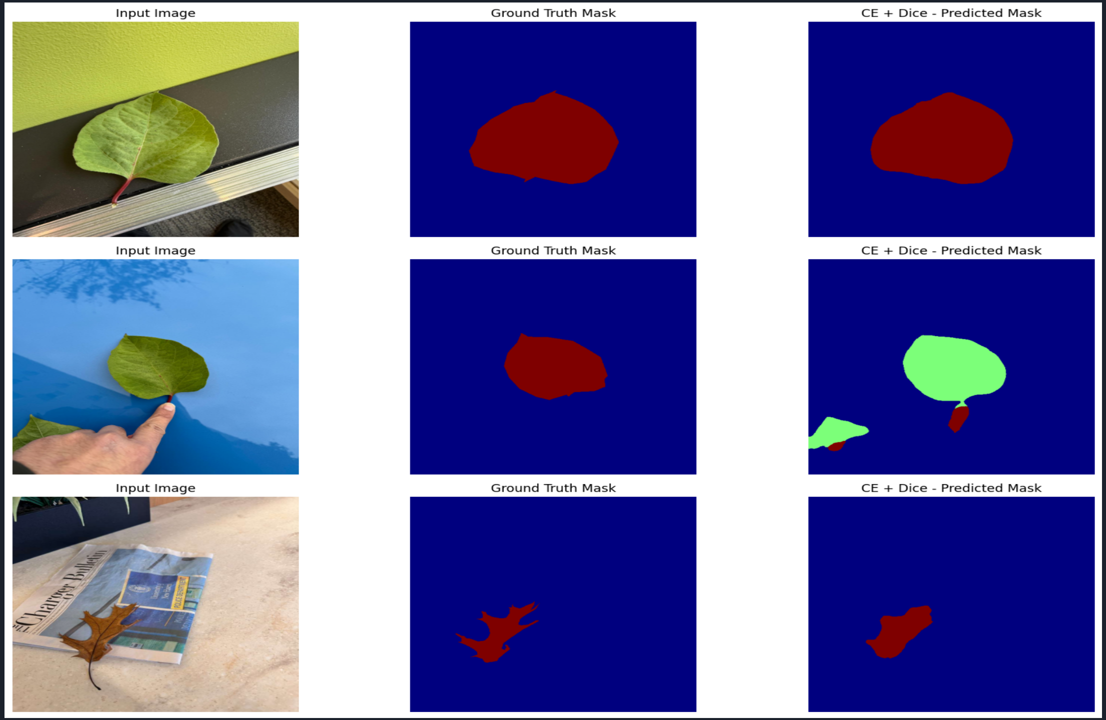
Results After Dice Loss (Improved Technique)

CE + Dice Fine-tuning

- Better dry leaf localization
- Fewer false negatives
- Improved boundary accuracy
- Higher IoU for minority class



Qualitative Results



Conclusion

Key Takeaways

- SegFormer effectively segments leaf health regions
- Strong results with small dataset
- Hyperparameter tuning improved baseline
- Dice Loss significantly improved dry-leaf detection
- Model can be extended to other plant diseases

References

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[4] A. Dosovitskiy *et al.*, "An Image is Worth 16×16 Words: Transformers for Image Recognition at Scale," *arXiv preprint arXiv:2010.11929*, 2020. https://arxiv.org/abs/2010.11929

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Thank you!