Comparing Object Detection, Instance Segmentation, and Semantic Segmentation for Automated Vegetation Detection in Railroad Systems

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Introduction

Motivation & Current Solution

140,000 miles

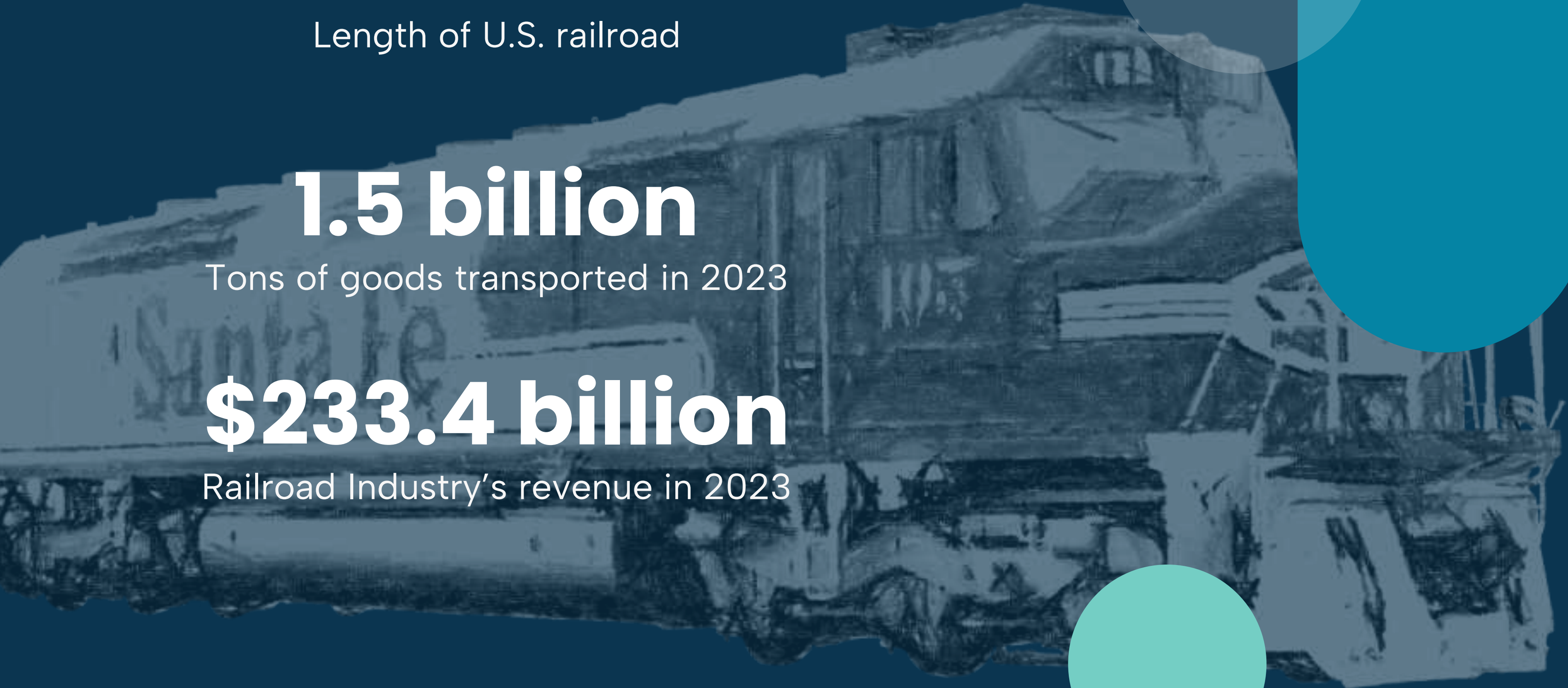
Length of U.S. railroad

1.5 billion

Tons of goods transported in 2023

$233.4 billion

Railroad Industry’s revenue in 2023



Consequences of Overgrown Vegetation

1
Fire Hazard

2
Slippery Rails

3
Track Deterioration

Current Solution

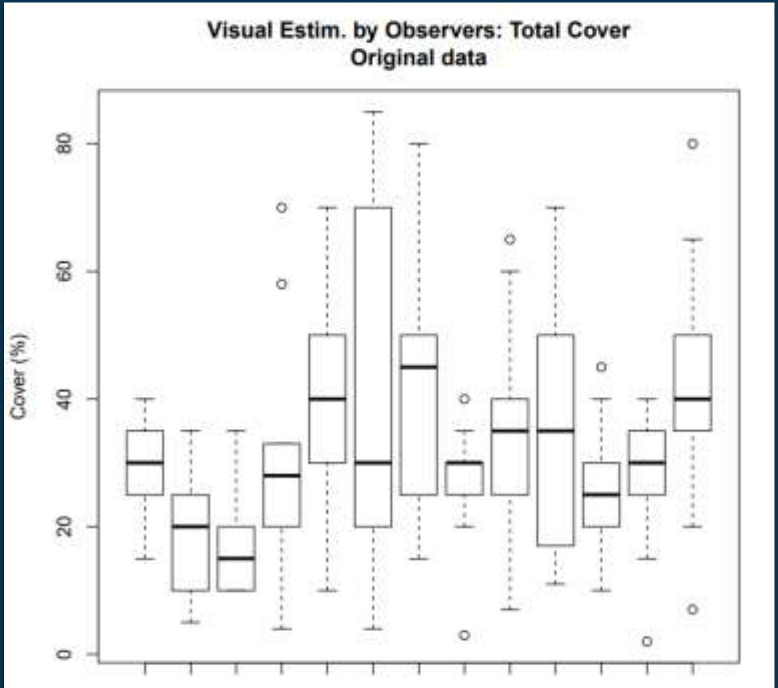
<u>Tradition methods of rail inspection</u>

Visual assessments conducted on site or through video footage

<u>This is a proven flawed method</u>

Nyberg et al. (2016)

Multiple ANOVA (Analysis of Variance) tests showed significant differences in mean rater estimates



Structural vs Organic Defects

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Research Objective + Methodology

Compare modern deep learning model (YOLOv8, U-Net, DeepLabv3+) functions

- Compare YOLO Object Detection vs Instance Segmentation methods
- Compare U-Net & DeepLabv3+ Semantic Segmentation methods

Comparing domain specific vs general dataset

500 domain-specific vegetation dataset
vs 3,857 general vegetation dataset

YOLOv8: Object Detection vs. Instance Segmentation

Why YOLOv8? -> Fastest single-stage detector, with proven reliability in railroad defect real-time detection

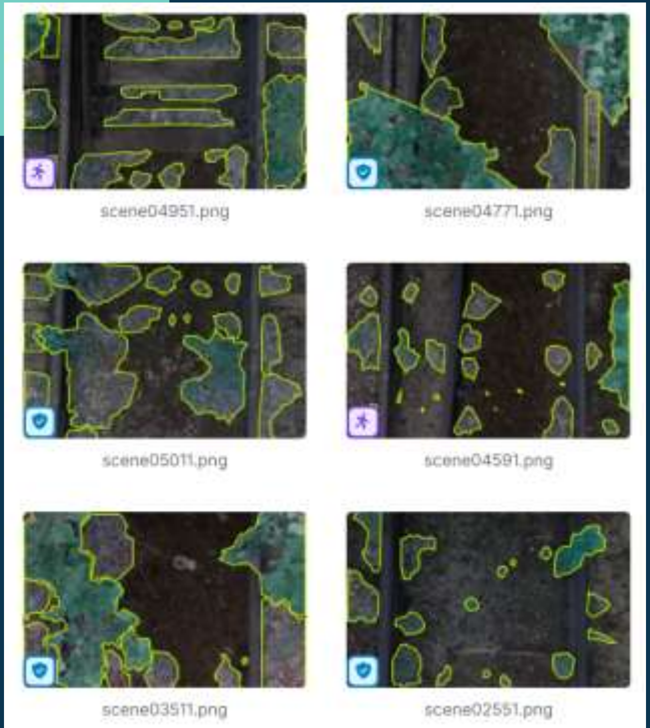
U-Net: Semantic Segmentation

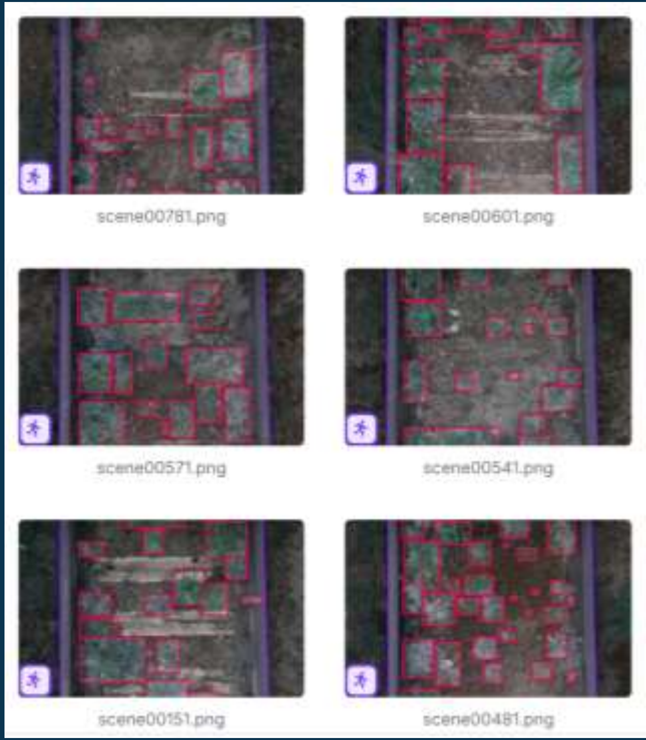
Why U-Net?-> U-shape encoder-decoder structure with skip connections preserves spatial detail during down sampling

DeepLabv3+: Semantic Segmentation

Why DeepLabv3+ -> U-shape encoder-decoder structure with skip connections preserves spatial detail during down sampling

Domain-Specific Dataset





500 railroad images at 5–15 mph using Intel RealSense D435, labeled in Roboflow (object + mask annotations)


4x4

General Vegetation Dataset

On top of the original dataset, datasets forked from Roboflow was used.
9,865 total images after augmentation (rotation, noise, crop, zoom)

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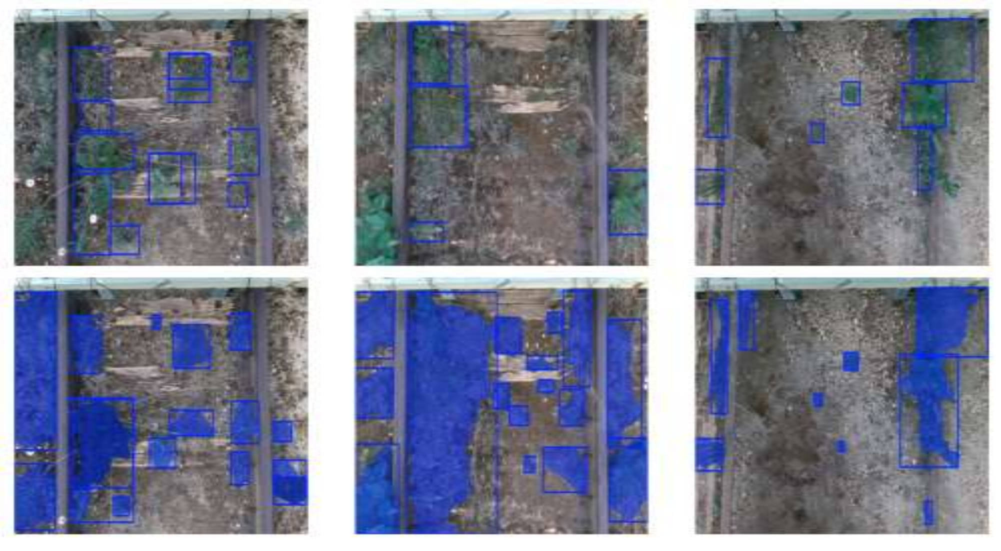
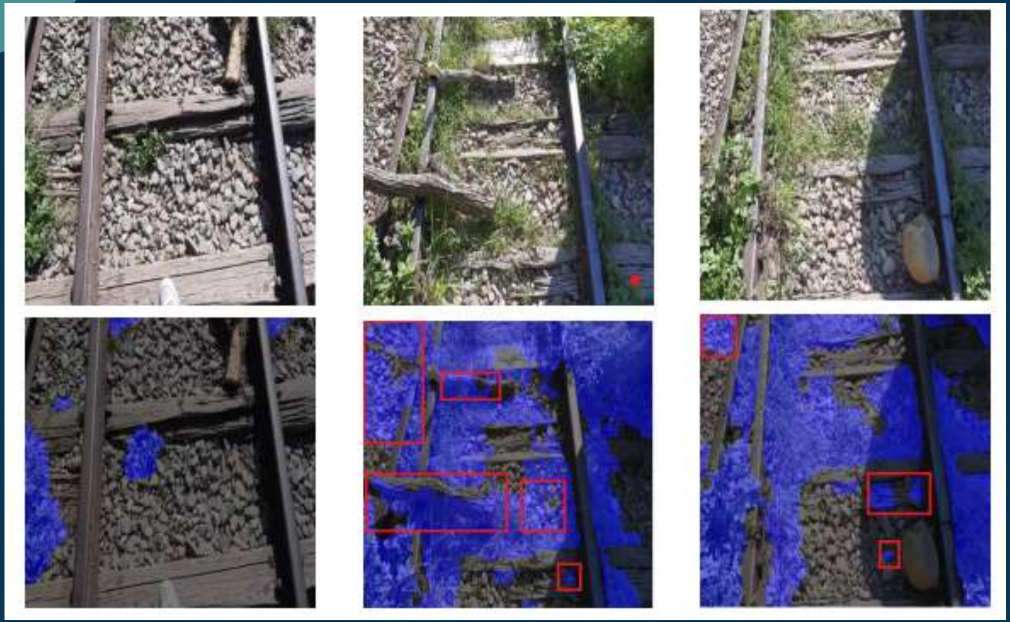
Results & Discussion

YOLOv8: Results



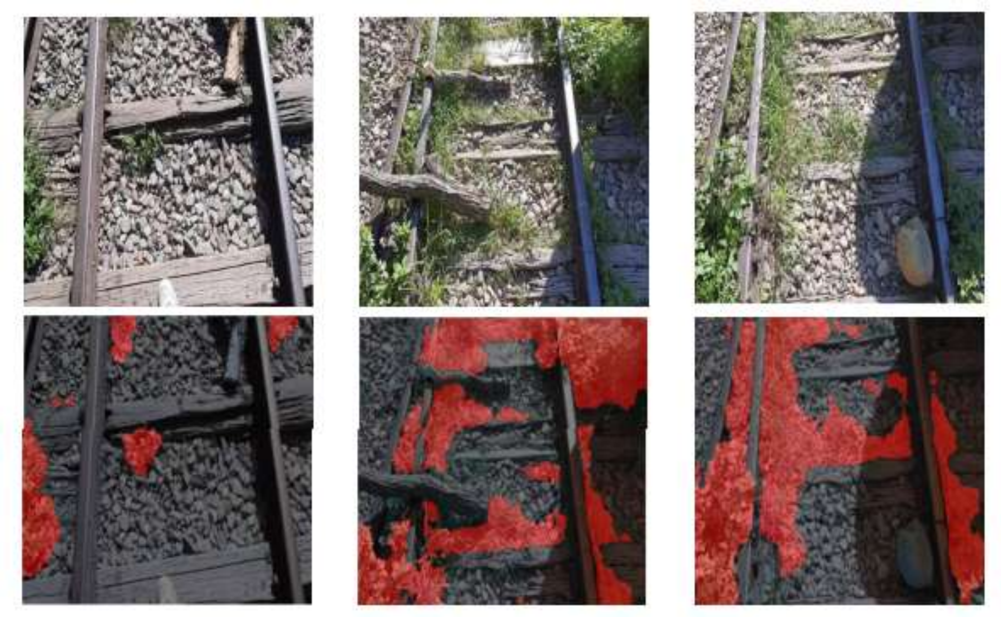
Metric	Object Detection	Segmentation
F1	0.69	0.72
Precision	1.00	1.00
Recall	0.88	0.86
mAP@0.5	0.68	0.73

U-net: Results



Metric	Value
Validation F1	0.8948
Validation Precision	0.9144
Validation Recall	0.8760
Validation IOU	0.8096
Validation Loss	0.1059

DeepLabv3+: Results



Metric	Value
Validation F1	0.9540
Validation Precision	0.9570
Validation Recall	0.9510
Validation IOU	0.9124
Validation Loss	0.053

Error Analysis

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Conclusion

Summary

- DeepLabv3+ achieved the best overall metrics (F1 = 0.9540)

- YOLOv8 Segmentation performed better than object detection, but still weaker than semantic segmentation models

- Semantic segmentation is more suitable for irregular vegetation detection

YOLO Training Obstacles

Training Changes which made F-1 score decrease:

- Tuned hyparameters
  - IOU, Epochs, Learning Rate
- Data Augmentation
- Changing YOLO versions, weight sizes, types of optimizers
- Refining & Editing datasets
- Including 3-5% null images in dataset

/content/Vegetation-with-only-collected-data_SAM_Annotated-2-1	414 images with only field data (segmentation); no tuned parameters; normal	no tuned parameters	(mask F-1 score) 0.71	upgrade	train3
/content/Vegetation-with-only-collected-data_SAM_Annotated-2-1	414 images with only field data (segmentation); no tuned parameters; normal	optimizer=SGD	(mask F-1 score) 0.71	-	train 4
/content/Vegetation-with-only-collected-data_SAM_Annotated-2-1	414 images with only field data (segmentation); no tuned parameters; normal	optimizer=AdamW	(mask F-1 score) 0.72	upgrade	train5
/content/Vegetation-with-only-collected-data_SAM_Annotated-2-1	414 images with only field data (segmentation); no tuned parameters; normal	yolov11n-seg	(mask F-1 score) 0.72	-	train6
/content/Vegetation-with-only-collected-data_SAM_Annotated-2-1	414 images with only field data (segmentation); no tuned parameters; medium	yolov8 n to m (weight size)	(mask F-1 score) 0.71	downgrade	train7

Future Work Considerations

- Integrate binary railway masks for selecting ROI

- Train YOLOv8 using general vegetation dataset & UNet/DeepLabv3+ using domain specific dataset

- Evaluating model variants

Thank You!

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