AI-Powered Semantic Segmentation for Landscape Understanding

Pixel-level environmental classification using deep learning — Presented by: [Aritra Sikder] • [Startathon] • [Aritra Sikder,Tanishq Srivastava]

Problem Statement

Manual Analysis Is Limited

Field and image annotation are time-consuming, subjective, and inconsistent across teams.

Scalability Gap

Human workflows cannot scale to continuous global monitoring or high-frequency sensor streams.

Our Goal

Build an automated model that assigns meaningful environmental labels to every pixel in landscape images.

Why This Project Matters

Environmental Monitoring

Track land-cover change and deforestation with precise spatial detail.

Precision Agriculture

Detect crop stress and heterogeneity at sub-field resolution for targeted interventions.

Disaster Assessment

Rapid damage mapping for floods, fires, and landslides to inform emergency response.

Autonomous Navigation

Support traversal decisions for robots and vehicles operating in natural environments.

What Is Semantic Segmentation?

Semantic segmentation assigns a class label to every image pixel, producing dense maps that reveal object boundaries and spatial context.

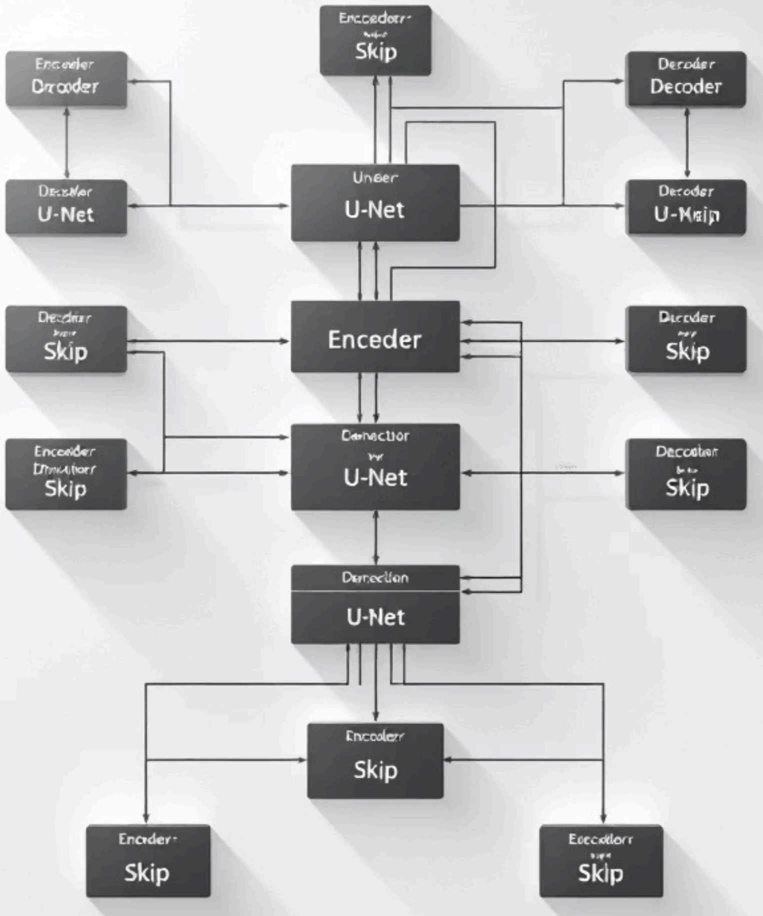
- Enables multi-class scene understanding (vegetation, water, soil, built features)
- Preserves fine spatial details via pixel-wise supervision
- Differs from detection: focus is on per-pixel semantics, not bounding boxes

Dataset Overview

High-resolution landscape images paired with pixel-accurate ground truth masks across multiple environmental classes.

- Classes: Trees, Bushes, Grass, Rocks, Water/Sky, Ground clutter
- Sources: drone, airborne, and satellite sensors — varied spectral and spatial resolutions
- Annotations: expert-labeled masks for per-pixel supervision and validation

Balanced sampling and labeled edge cases improve model generalization across ecosystems.



Model Architecture

U-Net with ResNet34 Encoder

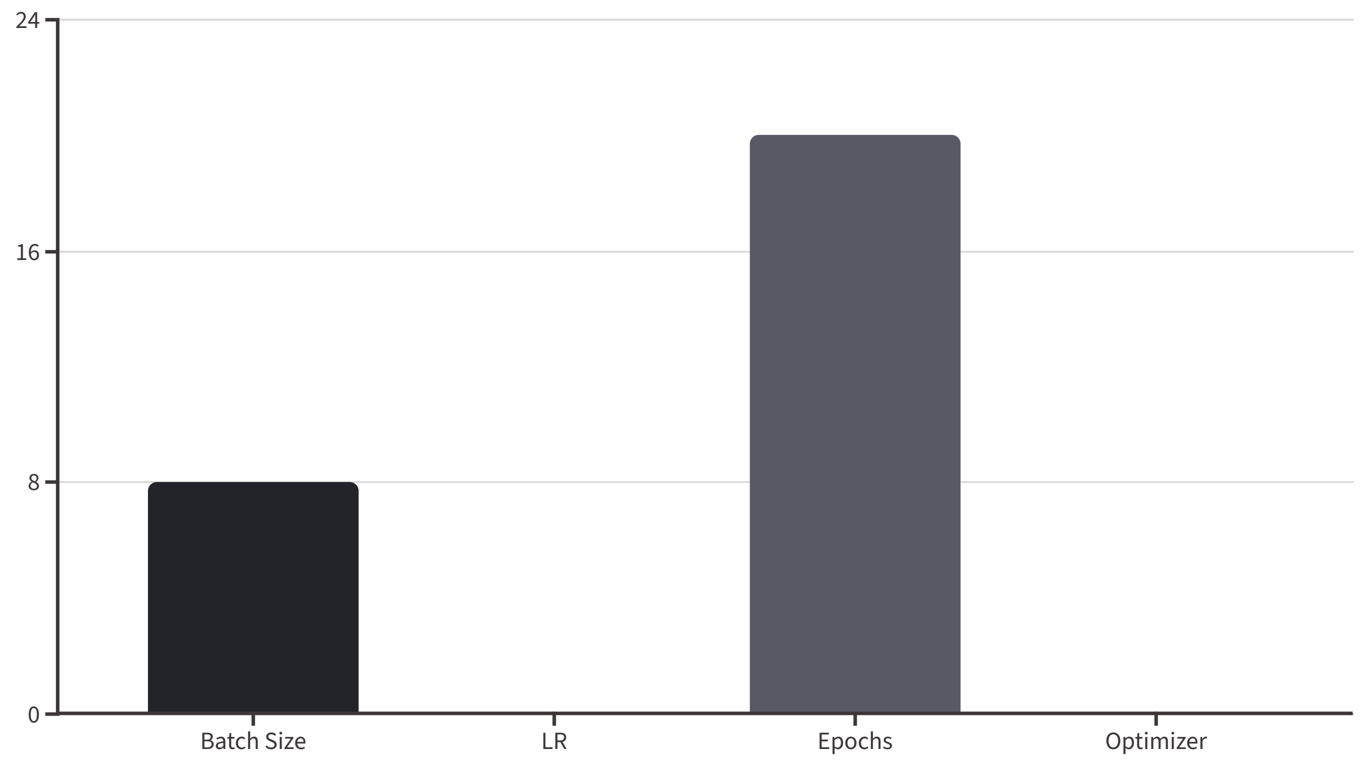
Encoder: ResNet34 pretrained backbone for strong feature extraction. Decoder: symmetric upsampling with skip connections to recover spatial detail.

Design Rationale

Transfer learning from ImageNet accelerates convergence and improves low-data performance; skip connections preserve fine-grain boundaries crucial for environmental classes.

Computational Balance

Architecture balances accuracy with practical GPU memory and inference time for medium-sized datasets.



Training Strategy

Hybrid loss: **Dice Loss** + **Cross Entropy** to jointly optimize overlap and per-class discrimination.

- Dice improves IoU and addresses class imbalance for sparse classes (e.g., rocks, water)
- Cross Entropy stabilizes per-pixel classification probabilities
- Data augmentation: geometric transforms, spectral jitter, cutmix-like masks to increase robustness

Per-class IoU **Mean IoU** **Visualize**

Evaluation uses Intersection over Union (IoU) per class, aggregated to mean IoU. IoU directly penalizes false positives and negatives, making it the industry standard for segmentation.

> Report per-class IoU alongside mean IoU to reveal class-specific weaknesses (e.g., thin vegetation vs. large sky regions).

Results & Observations

Model achieves strong boundary delineation and multi-class separation in heterogeneous scenes. Visual inspection: predicted masks closely match annotations, especially for contiguous vegetation and water.

- Strengths: accurate large-region segmentation, robust to seasonal texture changes
- Remaining issues: thin linear features and mixed pixels at canopy edges
- Suggested fixes: boundary-aware loss, higher-resolution inputs, targeted augmentation

Conclusion & Future Scope

Conclusion

We built a practical semantic segmentation pipeline that delivers pixel-level environmental labels with competitive IoU and real-world applicability for monitoring and decision support.

Near-Term Improvements

Explore DeepLabV3+, advanced augmentations, boundary-aware losses, and model ensembling to boost IoU on challenging classes.

Deployment

Optimize inference (quantization, pruning) for real-time edge deployment on drones and field devices; integrate into operational monitoring pipelines.

Next steps: run cross-domain validation, expand labeled datasets across biomes, and prepare a reproducible evaluation kit for competition judges.