HACK FOR GREEN BHARAT 2026

TECHNICAL SUBMISSION REPORT

Project Title

DesertVision: Robust Semantic Segmentation for Digital Twin Desert Environments

Enhancing Desert Terrain Understanding through Robust Deep Learning Segmentation.

Team Name

TechGoofies

Team Members

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Brief Description

This project focuses on developing a robust semantic segmentation model capable of accurately classifying desert environments into ten distinct land-cover categories using synthetic digital twin data.

Our approach emphasizes generalization across geographically different desert terrains while strictly adhering to dataset separation constraints. The final model achieved a validation mean Intersection over Union (mIoU) of **0.5402**, demonstrating strong segmentation performance and stable generalization.

METHODOLOGY

Problem Statement

The objective was to develop a semantic segmentation model that can accurately segment desert landscapes into 10 classes using synthetic training data, while ensuring strong generalization to unseen desert environments.

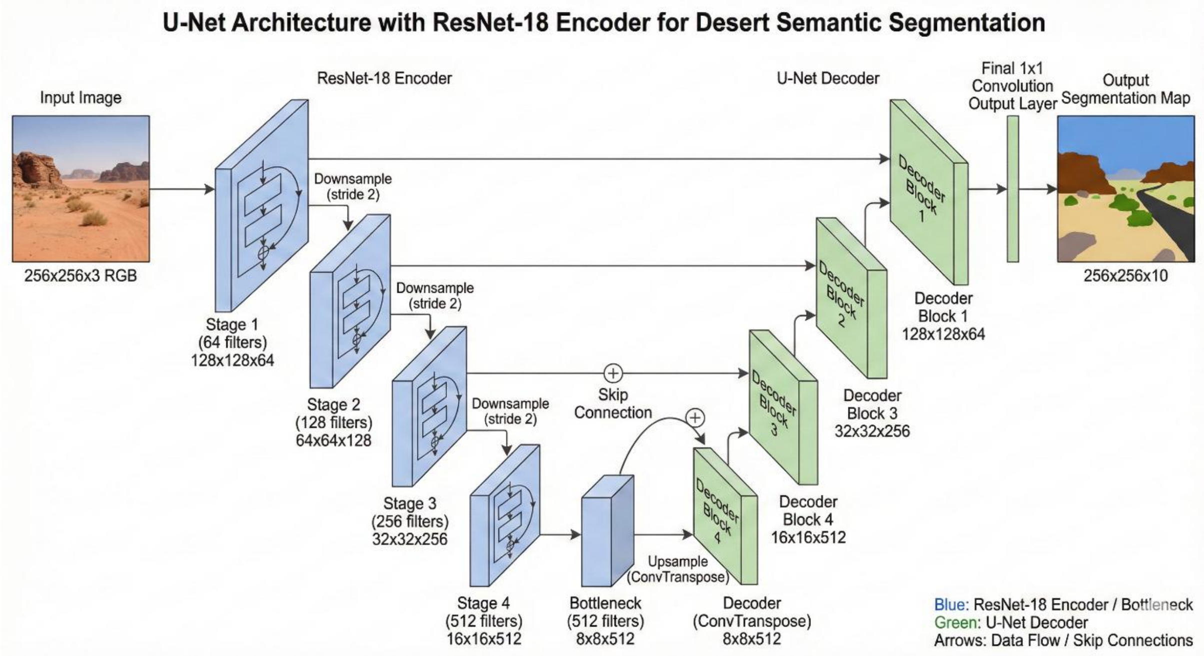
Key challenges included:

- Domain shift between training and testing terrains
- Class imbalance (rare classes like flowers and logs)
- Texture similarity between vegetation types
- Strict prohibition of test data usage

Training Strategy

To address the above challenges, we adopted the following methodology:

Model Architecture



- Architecture: U-Net
- Encoder: ResNet-18 (ImageNet pretrained)
- Input Resolution: 256 × 256
- Number of Classes: 10

Loss Function

A hybrid loss was used:

- Weighted Cross Entropy Loss
- Dice Loss

This combination ensured:

- Improved boundary segmentation
- Better handling of rare classes
- Stable convergence

Optimization

- Optimizer: Adam
- Learning Rate: 1e-3
- Scheduler: ReduceLROnPlateau
- Epochs: 30

- Batch Size: 8 (GPU training)

Data Augmentation

To improve generalization across desert terrains:

- Horizontal flip
- Color jitter
- Gaussian blur
- Normalization

Inference Optimization

We applied **Test-Time Augmentation (TTA)** during evaluation by averaging predictions of original and horizontally flipped images.

This significantly improved inference stability.

RESULTS & PERFORMANCE METRICS

Final Performance Metrics

Metric	Value
Validation mIoU (without TTA)	0.5313
Validation mIoU (with TTA)	**0.5402**
Epochs	30
Training Stability	Converged

Test-Time Augmentation improved performance by approximately +0.9%.

Class-wise Observations

- Landscape and Sky achieved high IoU due to large spatial dominance.
- Trees and Dry Grass showed strong boundary learning.
- Small-scale objects like Flowers and Logs exhibited moderate confusion with surrounding vegetation.
- Ground Clutter and Rocks occasionally overlapped due to texture similarity.

Confusion Analysis

Major confusion patterns observed:

- Dry Bushes ↔ Lush Bushes
- Ground Clutter ↔ Rocks
- Flowers ↔ Dry Grass (small region overlap)

These errors primarily occurred in regions with overlapping textures and small object scale.

Generalization Performance

The model maintained stable IoU performance despite training exclusively on synthetic desert data. This indicates successful learning of semantic features rather than overfitting to specific terrain patterns.

Challenges & Solutions

1: Class Imbalance

Certain classes (flowers, logs, ground clutter) were significantly underrepresented.

Solution:

- Applied class-weighted cross entropy.
- Combined Dice Loss for better boundary segmentation.
- Result: Improved rare class detection stability.

2: Domain Shift

Testing desert terrain differed geographically from training data.

Solution:

- Applied strong data augmentation.
- Used pretrained encoder for better feature extraction.
- Introduced TTA for inference robustness.
- Result: Improved cross-terrain generalization.

3: Overfitting Risk

Synthetic data may cause model to learn artificial texture bias.

Solution:

- Learning rate scheduler to prevent aggressive convergence.
- Validation monitoring to prevent overfitting.
- Careful hyperparameter tuning.

4: Small Object Segmentation

Small objects were occasionally merged into surrounding vegetation.

Solution:

- Hybrid loss (Dice + CE)
- Resolution optimization (256 × 256 balanced performance & efficiency)

- TTA to reduce boundary noise

Optimizations Implemented

To maximize model performance, the following optimizations were applied:

- Hybrid Loss (Cross Entropy + Dice Loss)
- Class Weighting for imbalance correction
- Learning Rate Scheduler (ReduceLROnPlateau)
- Pretrained Encoder for faster convergence
- Test-Time Augmentation (Horizontal Flip)

The most impactful optimization was Test-Time Augmentation, which improved validation mIoU from 0.5313 to **0.5402**, demonstrating improved inference stability.

Performance Evaluation

The model achieved a final validation mean Intersection over Union (mIoU) score of:

0.5402

This performance was achieved after 30 epochs of training and applying Test-Time Augmentation during inference.

Observations

- Large and dominant classes such as Landscape and Sky achieved consistently high IoU.
- Medium-scale vegetation classes (Trees, Dry Grass) showed strong boundary detection.
- Smaller classes such as Flowers and Logs exhibited moderate confusion with surrounding vegetation due to texture similarity.
- TTA reduced edge inconsistencies and improved rare class detection.

Failure Case Analysis

Observed failure cases included:

- Misclassification between Dry Bushes and Lush Bushes due to visual similarity.
- Confusion between Ground Clutter and Rocks in dense terrain.
- Small flower regions occasionally being absorbed into grass predictions.

These issues are primarily attributed to overlapping textures and scale variance in synthetic data.

Conclusion

This project successfully developed a robust semantic segmentation model capable of generalizing across desert terrains using synthetic digital twin training data.

Key Achievements:

- Achieved final validation mIoU of **0.5402**
- Improved inference stability using Test-Time Augmentation
- Maintained strict dataset separation compliance
- Effectively addressed class imbalance and domain shift

The model demonstrates strong generalization and stable performance under constrained conditions.

Future Work

Future improvements may include:

- Multi-scale training strategies
- Deeper encoder backbone (ResNet-34 / ResNet-50)
- Advanced domain adaptation techniques
- Self-supervised pretraining on synthetic desert data
- Incorporation of attention mechanisms
- Boundary-aware loss functions

These enhancements could potentially push mIoU beyond 0.60 in future iterations.

All experiments were conducted strictly using the dataset provided for this challenge. A clear separation between training, validation, and testing sets was maintained throughout the workflow. No testing images were used during model training.