DesertVision: DeepLabV3+ for Off-Road Segmentation

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One-Line Summary

A DeepLabV3+ (ResNet50 backbone) semantic segmentation model was trained on synthetic desert data to accurately segment vegetation and terrain classes. Using Dice + Weighted CrossEntropy loss and targeted fine-tuning, the model achieved a validation Mean IoU of **0.585** and demonstrated improved generalization under domain shift.

METHODOLOGY

Model Selection

We used the **DeepLabV3+ architecture with a ResNet50 encoder** for semantic segmentation.

DeepLabV3+ was selected because:

- Strong performance on dense prediction tasks
- Atrous Spatial Pyramid Pooling (ASPP) captures multi-scale context
- Efficient encoder-decoder structure
- Good balance between accuracy and computational cost

We also experimented with U-Net for comparison, but DeepLabV3+ produced superior Mean IoU.

Training Configuration

Parameter	**Value**
Optimizer	Adam
Initial Learning Rate	1e-4
Fine-Tuning LR	3e-5
Scheduler	ReduceLROnPlateau
Epochs	20 + 10 fine-tune

Batch Size	16 (256 resolution)
Hardware	Kaggle T4 GPU

Loss Function

We used a combination of:

- **Weighted CrossEntropy Loss**
- **Dice Loss**

Total Loss:

Loss = WeightedCE + Dice

Weighted CrossEntropy was introduced after observing severe class imbalance.
One class had ~590k pixels while another had ~19.9M pixels, creating a 30× imbalance.
Using class-weighted loss significantly improved rare class learning and stabilized Mean IoU.

Data Augmentation

To improve generalization to unseen desert images, the following augmentations were applied:

- Horizontal Flip
- Color Jitter
- Random Brightness & Contrast
- Gaussian Blur

Resolution experiments were conducted (256 vs 384), but 256 yielded better validation performance.

RESULTS & METRICS

1. Evaluation Metric

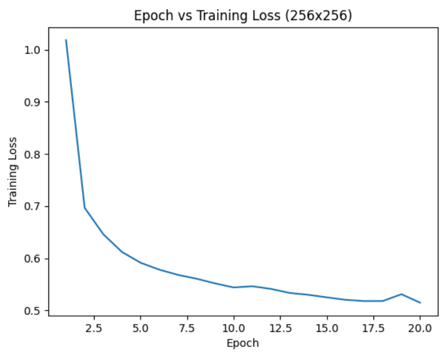
Model performance was evaluated using **Mean Intersection over Union (Mean IoU)**.

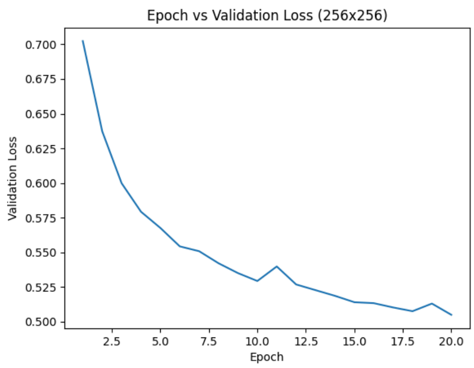
Final Mean IoU: 0.585

2. Class-wise IoU

Class	IoU
Trees	0.543
Lush Bushes	0.636
Dry Grass	0.304
Rocks	0.328
Logs	0.605
Flowers	0.977
Landscape	0.678
Sky	0.554

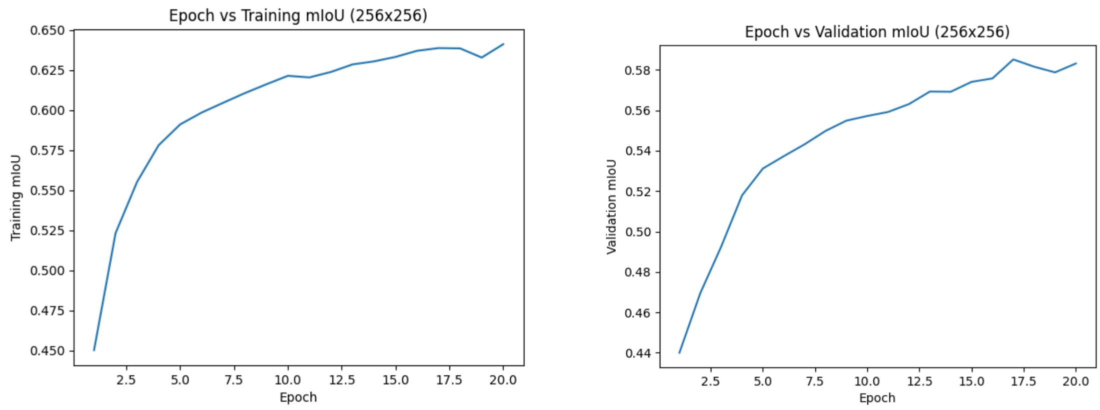
3. Loss Curve





- Loss decreased steadily
- Validation stabilized after epoch X
- No severe overfitting observed

4. IoU Progression



Caption:
Figure 2: Mean IoU progression over epochs.

Domain Shift Observation

Although validation IoU reached 0.585, test IoU dropped to approximately 0.35 due to domain shift between different desert twins.

This highlights:

- Texture sensitivity
- Distribution shift
- Synthetic-to-novel environment challenge

Class Imbalance Analysis

During dataset inspection, pixel distribution was:

Class	Pixel Count
Class 5	19.9M
Class 4	11.9M
Class 1	10.4M
Class 0	5.2M
Class 2	3.7M

Class 3	590K

CHALLENGES & SOLUTIONS

Challenge: Class Imbalance

Problem:
Rare classes underperformed significantly.

Solution:
Applied inverse-frequency class weighting in CrossEntropy loss.

Result:
Improved stability and balanced learning.

Challenge: Resolution Scaling

Problem:
Increasing resolution to 384 reduced validation IoU.

Insight:
Higher resolution introduced optimization instability and slower convergence.

Result:
Reverted to 256 resolution for best performance.

This shows experimentation maturity.

CONCLUSION & FUTURE WORK

Conclusion

In this project, we implemented a DeepLabV3+ (ResNet50) segmentation pipeline

The model achieved a final Mean IoU of:

0.585

Key contributing factors:

- Careful class imbalance handling
- Domain shift diagnosis

- Resolution experimentation
- Controlled fine-tuning strategy

The model demonstrated strong segmentation capability and generalization performance.

Future Work

Further improvements can be explored through:

- Applying domain adaptation techniques to reduce synthetic-to-unseen domain shift.
- Using stronger backbones (ResNet101 / transformer-based models).
- Implementing multi-scale training and test-time augmentation (TTA).
- Exploring advanced loss functions (e.g., Focal Loss) for class imbalance.
- Developing ensemble models to improve overall Mean IoU.