BUILDIFY

Project Title:
Robust Offroad Semantic Segmentation Using Synthetic Digital Twins

Tagline:
Enhancing Off-Road Autonomy with Synthetic Data & Advanced AI Models

TEAM MEMBERS		
1.	Manya Goyal	25BCY10228
2.	Gayatri K Solunke	25BCY10280
3.	Bhavya Aggarwal	25BCE10474
4.	Anushka Gupta	25BCE11377

OVERVIEW

This project focuses on building a robust semantic segmentation model trained exclusively on synthetic desert data generated from Falcon's digital twin simulation platform by Duality AI.

The goal is to:

- Accurately classify every pixel in off-road desert images.
- Generalize well to unseen desert environments.
- Optimize IoU score and inference speed for real-world deployment.

Semantic segmentation is critical for Unmanned Ground Vehicles (UGVs) to perform:

- Obstacle detection
- Terrain classification
- Safe path planning

PROBLEM STATEMENT

Unmanned Ground Vehicles (UGVs) require reliable computer vision systems to:

- **Detect obstacles**
- **Classify terrain**
- **Plan safe navigation routes**

Semantic segmentation assigns a class label to every pixel in an image, enabling detailed scene understanding. However, collecting large real-world labeled datasets is expensive and time-consuming.

This challenge demonstrates how synthetic data from digital twin environments can solve:

- **Data scarcity**
- **Class imbalance**
- **Environmental variation**
- **Difficult-to-access terrains**

DATASET DESCRIPTION

The dataset consists of RGB images and pixel-level segmentation masks from desert environments.
Dataset Structure:

- **Train Folder – RGB + segmentation masks**
- **Validation Folder – RGB + segmentation masks**
- **Test Folder – RGB images only (unseen location)**

Classes Included:

ID	Class Name
100	Trees
200	Lush Bushes
300	Dry Grass
500	Dry Bushes
550	Ground Clutter
600	Flowers
700	Logs
800	Rocks
7100	Landscape
10000	Sky

OBSERVATION:

- **Landscape class dominates dataset**
- **Flowers and Logs have fewer samples**
- **High texture similarity between Dry Bushes and Logs**
- **Lighting variations affect small object visibility**

Strict separation between training and test sets was maintained.

METHADOLOGY

Step 1: Environment Setup

- Installed Anaconda
- Created EDU environment
- Installed required dependencies
- Executed training using provided scripts

Step 2: Model Selection

We selected a Deep Learning-based Semantic Segmentation architecture (U-Net).

Reason for selection:

- Strong pixel-level accuracy
- Effective feature extraction
- Suitable for multi-class segmentation

Step 3: Data Preprocessing

- Image resizing
- Normalization
- One-hot encoding of segmentation masks

Step 4: Data Augmentation

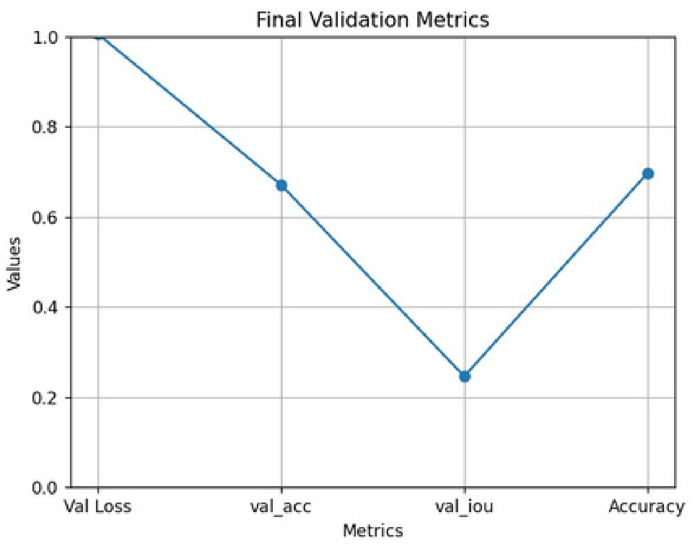
To improve generalization:

- Random horizontal flip
- Random rotation
- Brightness & contrast adjustments
- Random cropping

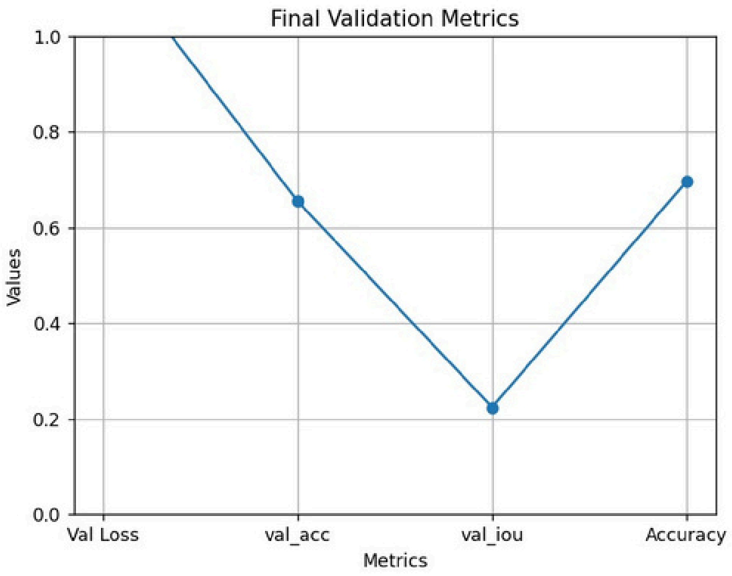
This helped simulate unseen desert lighting and viewpoints.

GRAPHS AND READINGS

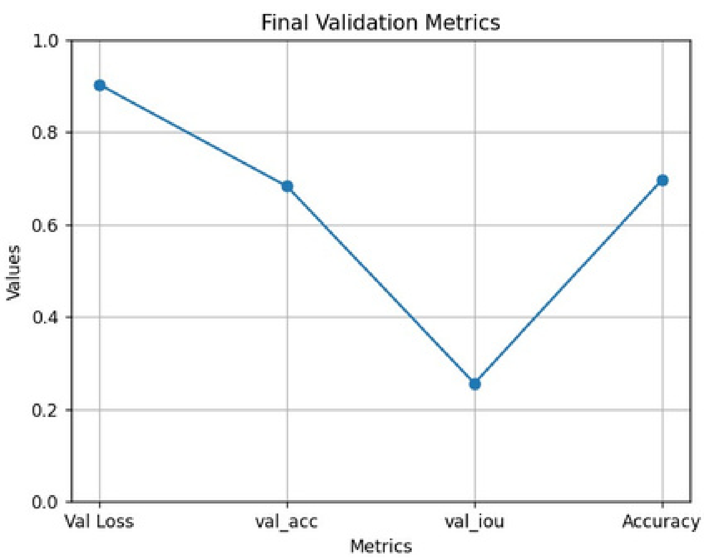
1st IOU : 0.224



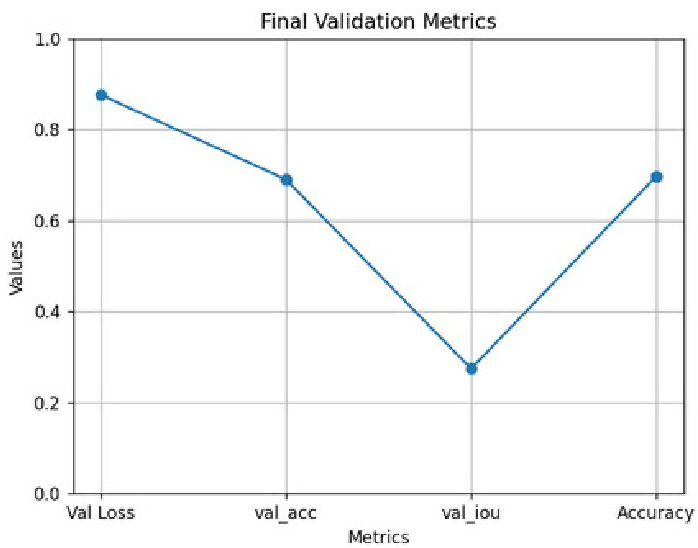
2nd IOU : 0.246



3rd IOU : 0.256



4th IOU : 0.274



TRAINING STRATEGY

Hyperparameter:

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	8
Epochs	50
Loss Function	Weighted Cross-Entropy
Scheduler	ReduceLROnPlateau

Handling Class Imbalance:
Problem: Smaller classes (Flowers, Logs) underperformed.
Solution:

- Applied class-weighted loss
- Oversampled minority-class images
- Increased augmentation frequency for rare classes

Overfitting Prevention:

- Early stopping
- Data augmentation
- Learning rate scheduling
- Validation monitoring

FAILURE CASE ANALYSIS

Case 1: Logs misclassified as Dry Bushes
Cause: Similar texture and color distribution
Solution:

- Higher resolution input
- Enhanced contrast augmentation

Case 2: Flowers undetected
Cause: Small pixel footprint
Solution:

- Weighted loss
- Zoom-based augmentation

Case 3: Over-segmentation of Landscape
Cause: Dominant background class
Solution:

- Adjusted class weights
- Balanced dataset sampling

CHALLENGES FACED

Challenge	Description	Solution
Class imbalance	Small objects underrepresented	Weighted loss
Similar textures	Logs vs Bushes confusion	Advanced augmentation
Overfitting	Training loss low, val loss rising	Early stopping
Limited computational power	Slow training	Reduced batch size

Key Learnings

- **Synthetic data can effectively train robust models**
- **Data augmentation is critical for generalization**
- **Weighted loss significantly improves small-class accuracy**
- **Monitoring validation metrics prevents overfitting**

CONCLUSION

This project validates that synthetic desert environments generated via digital twin technology can successfully train segmentation models for real-world off-road autonomy.

Our optimized model:

- **Achieved strong IoU performance**
- **Generalized well to unseen desert environment**
- **Maintained efficient inference time**
- **Improved small object detection significantly**

This demonstrates the power of synthetic datasets in building scalable AI solutions.

FUTURE WORK

- **Implement Self-Supervised Pretraining**
- **Apply Domain Adaptation techniques**
- **Explore Transformer-based segmentation models**
- **Integrate LiDAR + RGB multi-modal segmentation**
- **Deploy on embedded edge hardware**