# HACKATHON REPORT

**Project Name:** Desert Semantic Segmentation
**Team Name:** 404 Brain not Found
**Tagline:** AI-based pixel-level classification of desert terrain

## ➢ Problem

The goal of this project is to perform semantic segmentation on a synthetic desert dataset. The task involves classifying each pixel in an image into different terrain categories such as trees, rocks, sky, and ground.

This problem is challenging because different terrain elements often have similar textures and colors, making it difficult for the model to distinguish between them. Additionally, pixel-level classification requires high computational effort and precise learning.

The performance of the model is evaluated using the Intersection over Union (IoU) score, which measures how well the predicted segmentation matches the ground truth.

## ➢ Fix (Methodology / Approach)

To solve this problem, we used a deep learning-based approach with the U-Net architecture, which is well-suited for semantic segmentation tasks.

Key steps taken:

- Images and masks were loaded from the dataset

- Masks were mapped to class indices

- All images were resized to 256×256

- Data was normalized for better training

- Model was trained using PyTorch framework

- Loss function used: CrossEntropy Loss

- Optimizer used: Adam

Due to hardware limitations (CPU-based system), the dataset size and number of epochs were controlled to ensure faster training.

A GUI interface was also developed using Tkinter to visualize predictions in a user-friendly way.

## ➢ Results & Performance Metrics

The model was evaluated using the IoU (Intersection over Union) metric.

Observations:

- Training loss decreased across epochs

- Model learned basic segmentation patterns

- Outputs showed clear separation of terrain regions

Although training was limited, the model produced reasonable segmentation outputs.

Example outputs include:

- Original image

- Predicted segmentation mask

## ➢ Challenges & Solutions

**Challenges:**

- Slow training due to CPU-only execution

- Large dataset increased processing time

- Difficulty in distinguishing similar terrain types

- Initial errors during code execution and setup

**Solutions:**

- Reduced dataset size for faster experimentation

- Limited epochs for quick training

- Added debug statements to track execution

- Fixed file path and environment issues

These steps helped in successfully training the model and generating outputs.

## ➢ Conclusion & Future Work

This project demonstrates the application of deep learning in semantic segmentation of desert environments. The model was able to perform pixel-wise classification and generate meaningful outputs.

However, there is room for improvement. Future work can include:

- Increasing training epochs for better accuracy

- Using GPU for faster computation

- Applying advanced loss functions (Dice Loss, Weighted Loss)

- Adding more data augmentation techniques

- Improving IoU score

Overall, the project provides a solid foundation for real-world applications such as autonomous navigation and terrain analysis.