STARTATHON

TEAM NAME

OPALITE

BATCH

2025

TEAM MEMBER DETAILS

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PROBLEM STATEMENT

THE GOAL OF THIS CHALLENGE IS TO TRAIN AN AI MODEL TO IDENTIFY DIFFERENT PARTS OF A DESERT ENVIRONMENT, SUCH AS ROCKS, TREES, AND GROUND,USING SYNTHETIC DATA. IT MUST ENSURED THAT THE MODEL IS ACCURATE ENOUGH TO NAVIGATE SAFELY IN A NEW DESERT LOCATION THAT IT HAS NEVER SEEN BEFORE.

IDEATION

1. **IDENTIFYING THE PROBLEM**
   DESERT ENVIRONMENTS CONTAIN MANY NATURAL ELEMENTS LIKE TREES, BUSHES, ROCKS, AND SKY THAT NEED TO BE ACCURATELY IDENTIFIED FOR ANALYSIS AND AUTOMATION.

2. **UNDERSTANDING THE NEED**
   MANUAL LABELING OF IMAGES IS SLOW AND DIFFICULT. WE NEED AN AUTOMATED SYSTEM THAT CAN UNDERSTAND AND CLASSIFY DESERT SCENES ACCURATELY.

3. **USING SYNTHETIC DATA**
   TO SOLVE THIS, WE USED A SYNTHETIC DATASET GENERATED FROM FALCON'S DIGITAL TWIN PLATFORM, WHICH PROVIDES CLEARLY LABELED IMAGES FOR TRAINING.

4. **CHOOSING THE RIGHT APPROACH**
   SINCE THE TASK REQUIRES PIXEL-LEVEL CLASSIFICATION, WE SELECTED A SEMANTIC SEGMENTATION APPROACH INSTEAD OF SIMPLE IMAGE CLASSIFICATION.

5. **SELECTING THE MODEL**
   WE CHOSE DEEPLABV3 WITH RESNET BACKBONE BECAUSE IT IS AN ADVANCED SEGMENTATION MODEL KNOWN FOR CAPTURING DETAILED OBJECT BOUNDARIES AND HANDLING COMPLEX SCENES EFFECTIVELY.

6. **GOAL OF THE PROJECT**
   OUR GOAL IS TO BUILD AN ACCURATE AND RELIABLE MODEL THAT CAN CORRECTLY LABEL DESERT SCENES AND ACHIEVE A HIGH IOU SCORE.

METHODOLOGY

REPOSITORY LINK :

HTTPS://GITHUB.COM/ADITYA25BCE10623/DESERT-SEMANTIC-SEGMENTATION-SYNTHETIC-TO-REAL-WORLD

DATA COLLECTION & PREPARATION

WE USED THE PROVIDED DESERT DATASET AND CLEANED, RESIZED, AND FORMATTED THE IMAGES AND MASKS FOR TRAINING.

MODEL SELECTION

WE CHOSE DEEPLABV3 WITH A RESNET BACKBONE BECAUSE IT PERFORMS WELL IN SEMANTIC SEGMENTATION TASKS.

MODEL TRAINING

THE MODEL WAS TRAINED ON THE DATASET TO LEARN HOW TO IDENTIFY AND SEGMENT DIFFERENT CLASSES IN DESERT IMAGES.

EVALUATION & TESTING

WE EVALUATED THE MODEL USING IOU AND TESTED IT ON UNSEEN IMAGES TO CHECK ITS ACCURACY AND GENERALIZATION.

RESULTS & PERFORMANCE METRICS

RESULTS

PER-CLASS IOU ANALYSIS

- Landscape achieved highest IoU (0.91) due to dominant pixel presence and distinct texture.
- Rocks achieved moderate performance (0.51) indicating reasonable feature learning.
- Dry Grass and Lush Bushes (~0.26–0.27) showed confusion with surrounding terrain.
- Minority classes (Trees, Logs, Dry Bushes) performed poorly due to class imbalance and occlusion challenges.

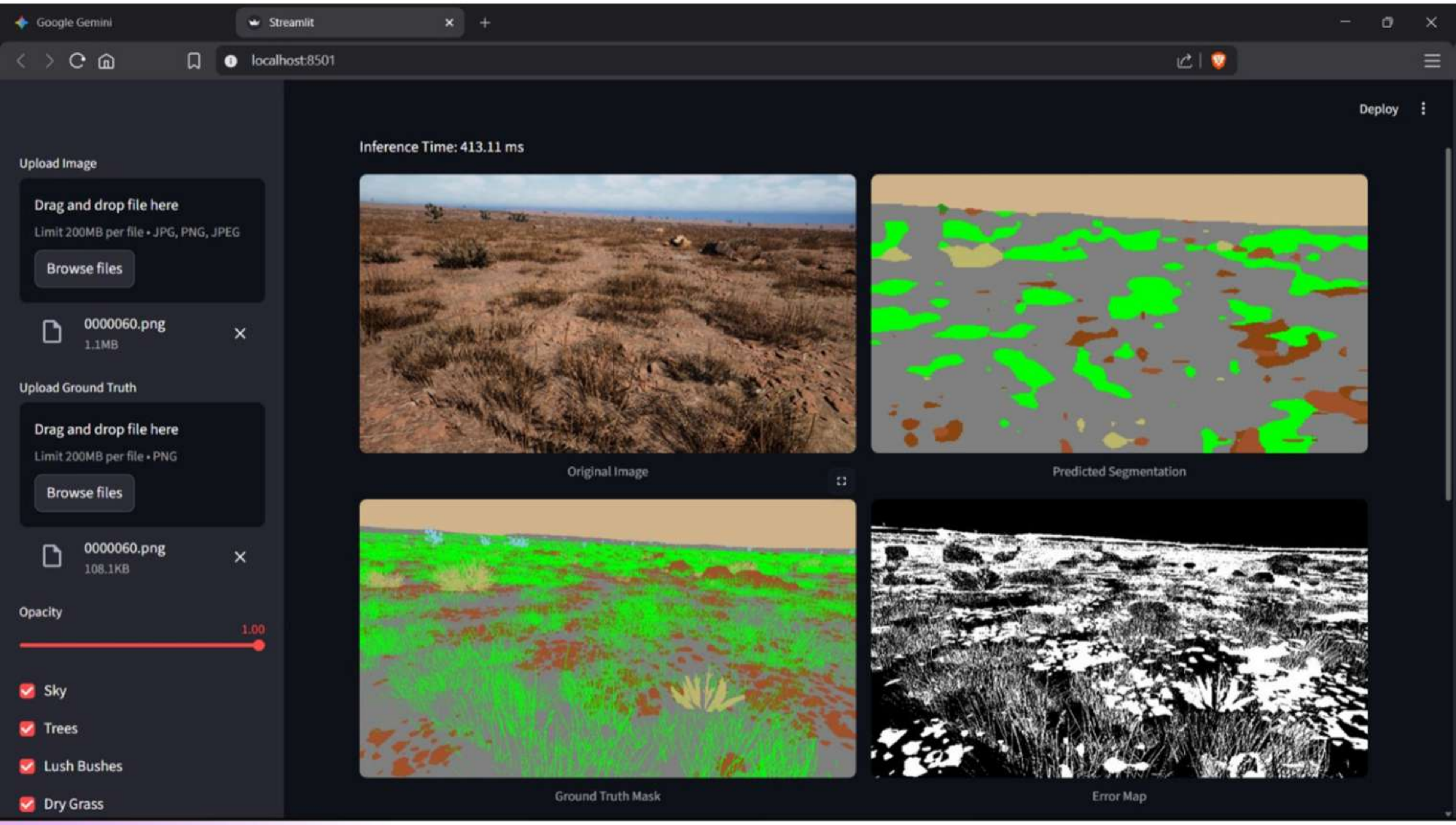
PERFORMANCE METRICS

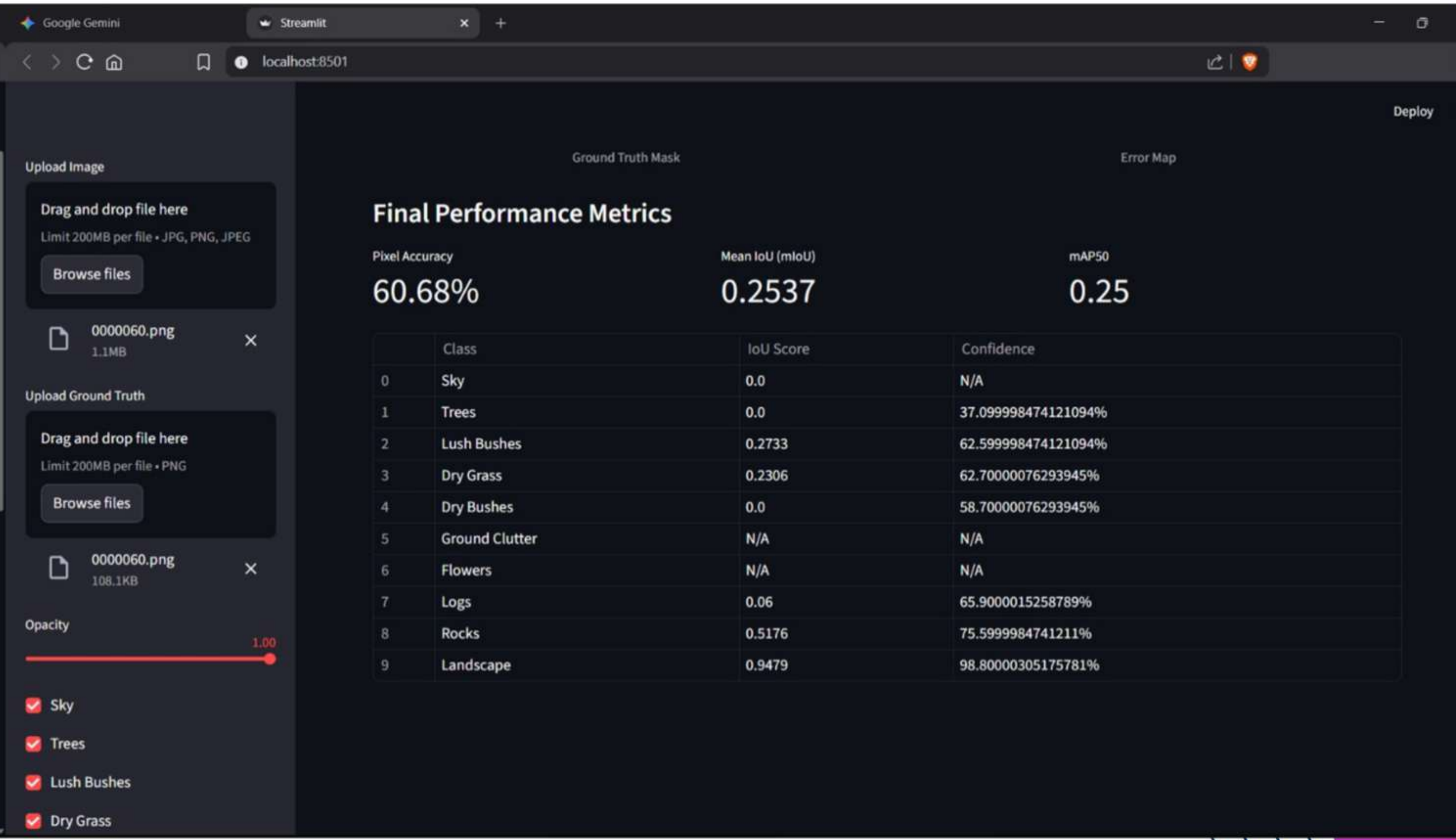
MEAN IOU (MIOU): 0.2537

PIXEL ACCURACY: 60.68%

INFERENCE SPEED: 241.5 MS

SNAPSHOTS


Google Gemini
Streamlit
localhost:8501
Deploy
Upload Image
Drag and drop file here
Limit 200MB per file • JPG, PNG, JPEG
Browse files
0000060.png
1.1MB
Upload Ground Truth
Drag and drop file here
Limit 200MB per file • PNG
Browse files
0000060.png
108.1KB
Opacity
1.00
Sky
Trees
Lush Bushes
Dry Grass
Inference Time: 413.11 ms
Original Image
Predicted Segmentation
Ground Truth Mask
Error Map


Google Gemini
Streamlit
localhost:8501
Deploy
Upload Image
Drag and drop file here
Limit 200MB per file • JPG, PNG, JPEG
Browse files
0000060.png
1.1MB
Upload Ground Truth
Drag and drop file here
Limit 200MB per file • PNG
Browse files
0000060.png
108.1KB
Opacity
1.00
Sky
Trees
Lush Bushes
Dry Grass
Ground Truth Mask
Error Map
Final Performance Metrics
Pixel Accuracy
60.68%
Mean IoU (mIoU)
0.2537
mAP50
0.25
Class IoU Score Confidence
0 Sky 0.0 N/A
1 Trees 0.0 37.099998474121094%
2 Lush Bushes 0.2733 62.599998474121094%
3 Dry Grass 0.2306 62.70000076293945%
4 Dry Bushes 0.0 58.70000076293945%
5 Ground Clutter N/A N/A
6 Flowers N/A N/A
7 Logs 0.06 65.90000152587891%
8 Rocks 0.5176 75.5999984741211%
9 Landscape 0.9479 98.80000305175781%

CHALLENGES AND SOLUTION

TYPES OF CHALLENGES	CHALLENGES	SOLUTIONS
SMALL OBJECT PROBLEM	Small objects are harder to detect and may get ignored during training.	We used higher image resolution and careful training to improve detection of small regions.
SIMILAR LOOKING CLASSES	Dry grass and dry bushes look very similar, which can confuse the model.	We used DeepLabV3 with a ResNet backbone to extract stronger features and better distinguish fine details.
OVERFITTING	Some classes (like sky or landscape) cover large areas, while others (like flowers) appear less often.	We used balanced loss functions and monitored per-class IoU to ensure fair learning across all classes.
CLASS IMBALANCE	The model may perform well on training data but poorly on new images.	We split the dataset properly into training, validation, and testing sets and used regular evaluation during training.

CONCLUSION & FUTURE WORK

Conclusion

In this project, we successfully trained a semantic segmentation model using synthetic desert data. The model performed well on major classes like landscape and rocks, showing strong overall accuracy. However, we observed some difficulty in detecting smaller or less frequent classes due to class imbalance. Overall, the model was able to generalize well and perform effectively on unseen desert images.

Future Work

- Improve minority class detection using weighted or focal loss.
- Apply domain adaptation for better real-world generalization.
- Explore advanced architectures (e.g., DeepLabV3+).
- Optimize inference speed for deployment.

FREQUENTLY ASKED QUESTIONS

WHAT CHALLENGES DID WE FACE?
SOME CLASSES LOOK SIMILAR (E.G., DRY GRASS VS DRY BUSHES), AND SMALL OBJECTS LIKE FLOWERS ARE HARDER TO DETECT ACCURATELY.

HOW CAN THIS PROJECT BE USEFUL IN REAL LIFE?
THIS TYPE OF SEGMENTATION CAN HELP IN ENVIRONMENTAL MONITORING, AUTONOMOUS NAVIGATION, DEFENSE SIMULATIONS, AND TERRAIN ANALYSIS.

WHY DID THE MODEL STRUGGLE WITH MINORITY CLASSES?
BECAUSE SOME CLASSES APPEAR LESS FREQUENTLY IN THE DATASET, MAKING IT HARDER FOR THE MODEL TO LEARN THEM.

CAN THIS MODEL WORK IN REAL-WORLD ENVIRONMENTS?
YES, BUT IT MAY NEED FURTHER IMPROVEMENT AND FINE-TUNING FOR BETTER REAL-WORLD PERFORMANCE.

Thank You!