AI-Driven Hazard Detection on Chandrayaan-3 Lunar Imagery Using Semantic Segmentation

K Mrudula Reddy, Ishitha Busetty, Ishaan C
Department of Computer Science and Engineering
R. V. College of Engineering, Bengaluru, India
Emails: kmrudulareddy.cs23@rvce.edu.in, ishithabusetty.cs23@rvce.edu.in, ishaanc.cs23@rvce.edu.in

***Abstract*—Safe lunar landing requires highly accurate detection of hazardous terrain features such as craters, rocks, uneven regolith, and dark shadow regions. Traditional image-processing techniques used in lunar landers struggle under extreme illumination variations and cannot perform robust pixel-wise hazard classification. This paper presents an AI-driven hazard detection system built using a U-Net-based semantic segmentation model trained on Chandrayaan-3 imagery. Segmentation masks were generated using the Segment Anything Model (SAM), enabling the creation of a high-quality dataset of 115+ annotated lunar surface images. The model achieves an IoU of 55%, demonstrating promising segmentation capability. The approach is lightweight and suitable for near–real-time inference, supporting future development of autonomous landing and navigation systems for lunar and planetary missions.**

***Index Terms*—Chandrayaan-3, Hazard Detection, Semantic Segmentation, U-Net, SAM, Lunar Terrain, Deep Learning**

I. Introduction

Lunar landing requires accurate identification of safe and unsafe regions during descent. The Chandrayaan-3 mission highlighted the importance of robust hazard detection, especially near the lunar south pole where lighting is extremely uneven and shadows dominate large areas.

Conventional hazard detection approaches rely on digital elevation maps (DEMs), slope estimation, or handcrafted filters. These methods often fail in low-light imagery, lack generalization, and cannot perform reliable pixel-level terrain classification. Deep learning-based semantic segmentation offers a powerful alternative by enabling dense hazard mapping directly from camera images.

This work develops an end-to-end AI pipeline using Chandrayaan-3 imagery, SAM-based annotations, and a U-Net architecture to classify terrain into hazardous and navigable regions.

II. Objectives

- Build a high-quality lunar terrain hazard dataset using SAM-based annotations.
- Train an optimized U-Net model for pixel-level terrain segmentation.
- Achieve near real-time inference suitable for embedded deployment.
- Maintain high segmentation accuracy for craters, rocks, and safe terrain.
- Implement a complete system pipeline from annotation to inference.

III. Methodology

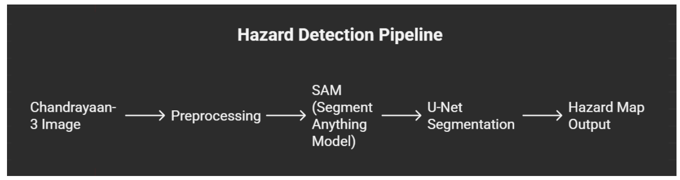

Fig. 1. Overall hazard detection pipeline: image acquisition, SAM annotation, U-Net segmentation, hazard map generation, inference.

A. Dataset Preparation

A dataset of 115+ Chandrayaan-3 surface images was curated. Using the Segment Anything Model (SAM), pixel-wise masks were generated for:

- Navigable terrain
- Rocks and obstacles
- Crater depressions

This significantly reduced manual annotation time while maintaining high precision.

B. Model Architecture

A U-Net encoder–decoder structure was adopted due to its strong performance in biomedical and remote sensing segmentation tasks. Skip connections allow recovery of spatial features lost during downsampling.

C. Training Pipeline

The U-Net model was trained using:

- Hybrid Dice + CrossEntropy loss
- Data augmentation (rotation, flipping, brightness change)
- Adam optimizer with learning rate tuning

D. Model Optimization

To prepare for embedded deployment, pruning and model simplification techniques were applied to reduce parameters and computational load.

E. Inference Integration

A real-time inference pipeline was built to generate:

- Hazard maps
- Confidence heatmaps
- Safety metrics

A Streamlit interface was developed to visualize segmentation outputs interactively.

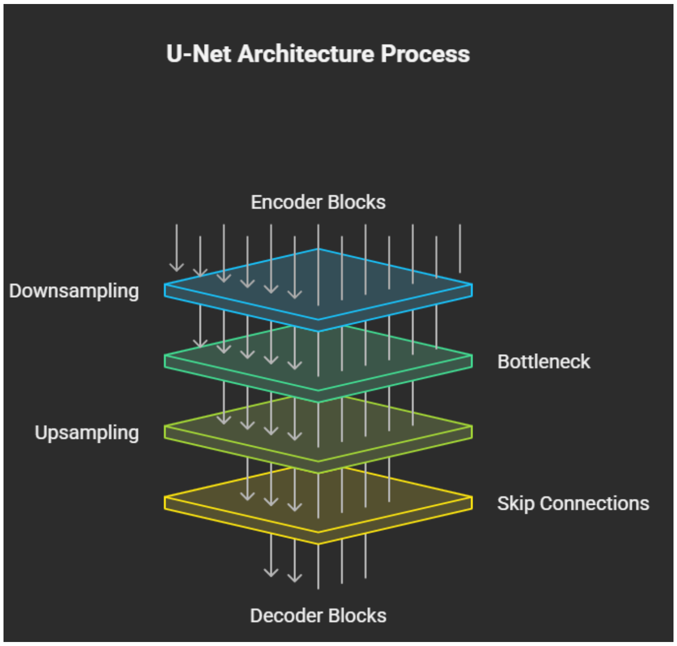

Fig. 2. U-Net architecture used for lunar terrain segmentation.

IV. Partial Implementation

The following components have been successfully implemented:

- SAM-based annotation for 115+ Chandrayaan-3 images.
- U-Net model implemented and trained on annotated dataset.
- Achieved IoU of 55% — indicating good segmentation quality with scope for refinement.
- Real-time inference functional (0.2 seconds per image on GPU).
- Streamlit demo interface for user-friendly visualization.

V. Conclusion

This work demonstrates a lightweight deep-learning pipeline for hazard detection on Chandrayaan-3 terrain images. SAM-assisted annotation and U-Net segmentation provide promising early results, achieving pixel-level hazard classification with reasonable accuracy. Future improvements include dataset expansion, transformer-based models, improved IoU, and benchmarking on embedded hardware for onboard mission deployment.

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