7th IEEE International Conference on Recent Advances and Innovations in Engineering
7th IEEE ICRAIE 2022

Semantic Segmentation on Martian Terrain for Navigation using Transformers

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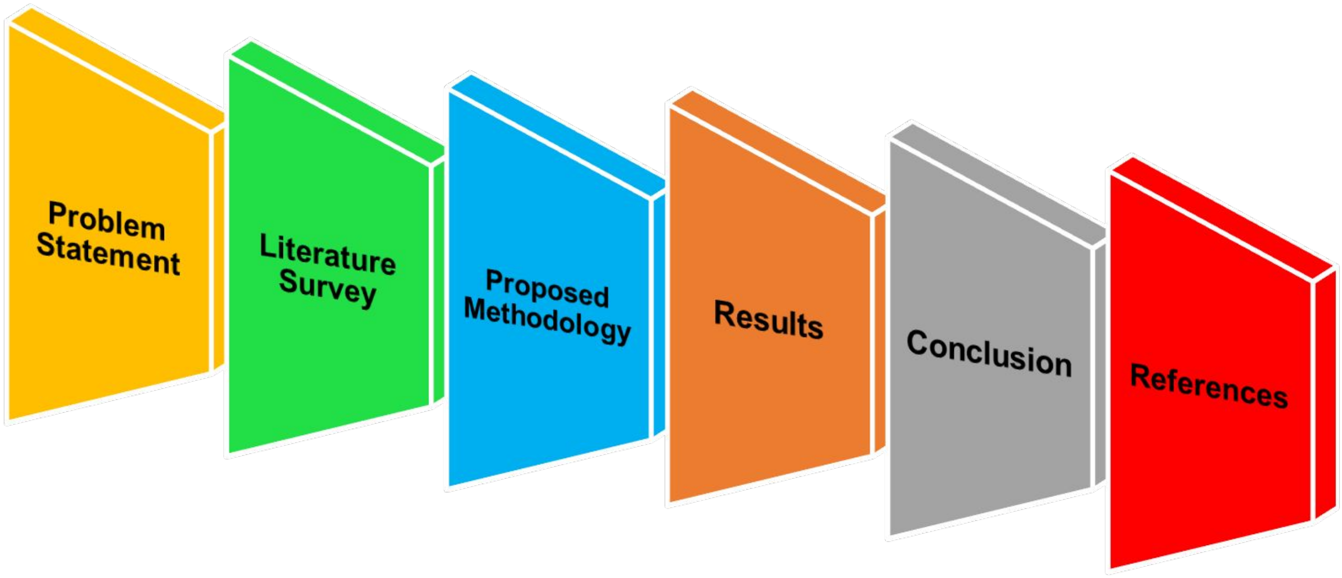
Agenda



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Problem Statement

Sandy Slumps
Sharp Rocky
Surface

Many methodologies have been implemented.

No approaches using **Vision Transformers (ViT)**

An **Autonomous Navigation System** focusing on the **Martian terrain**.

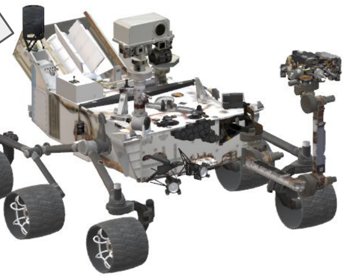
SOJOURNER

OPPORTUNITY

SPIRIT

CURIOSITY

PERSEVERANCE



“An alternative approach using the images captured by Rovers to Semantically Segment the Martian terrain for Navigation”

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Literature Survey

- With a focus on geological relevance rather than navigation, the majority of related research studies place an emphasis on categorising and classifying images of Martian topography from Mars imagery.
- On the rover images, experiments using Convolutional Neural Network, Support Vector Machines and K-means Clustering models have been conducted as seen in the past.
- AI4Mars data trained on DeepLabv3 model with labelling of images from Curiosity, Opportunity, and Spirit rovers, collected through crowdsourcing.
- SPOC employed Deep CNN on orbital and ground based imageries with terrain types of soil, rock and terrain features of scarp, ridges
- This work distinguishes itself from others in that it employs semantic segmentation using the **SegFormer** model.

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Proposed Methodology

Dataset

- The **AI4Mars** dataset includes majority of the existing high-resolution martian surface images.
- Comprises of ~35K MSL images sourced from:
  - Curiosity, Opportunity, and Spirit rovers.
  - Grayscale navigation camera (NAVCAM)
  - Color mast camera (Mastcam)
- Objective of AI4Mars is to train deep neural networks for sustainable self-driving on Mars.
  - Help future Martian rovers navigate the planet's surface.
- From MSL NAVCAM data, **18,130 raw images** are used for this problem statement.

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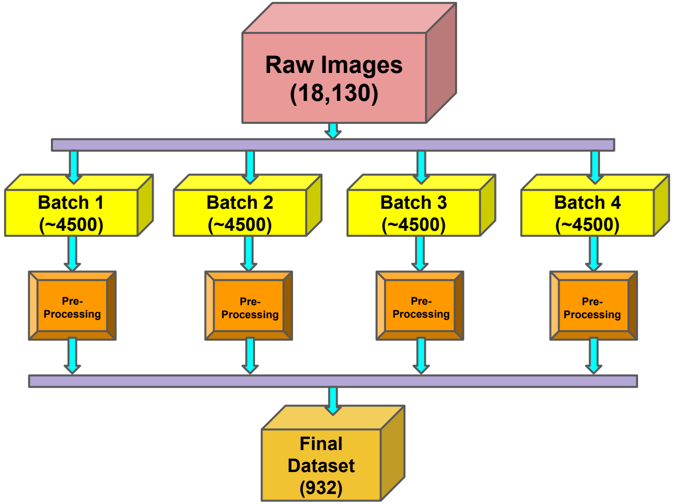
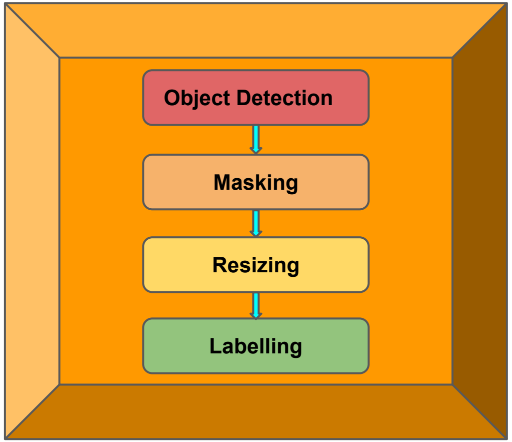
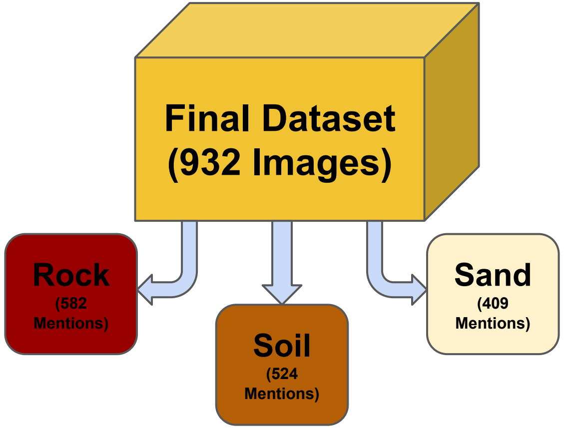
Pre-Processing







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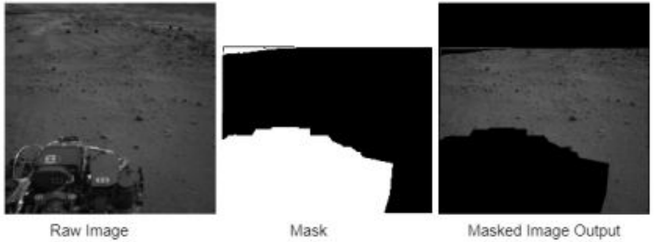
- **Object Detection:**
  - Area of the greatest bounding box formed around the detected rover > ¼(image size) -> **Image Rejected** from batch
  - Area of the greatest bounding box formed around the detected rover < ¼(image size) Or No rover found -> **Image retained** in the batch
  - **10,041 images** were retained from original 18,130 images
- **Masking:**
  - **Unwanted regions** were masked - sky / rover components
- **Resizing:**
  - Each image was downsized to **512x512** from original 1024x1024
- **Labeling:**
  - Each image was labeled into **3 classes - Rock, Soil, Sand**
  - Final Dataset with **932 Images**



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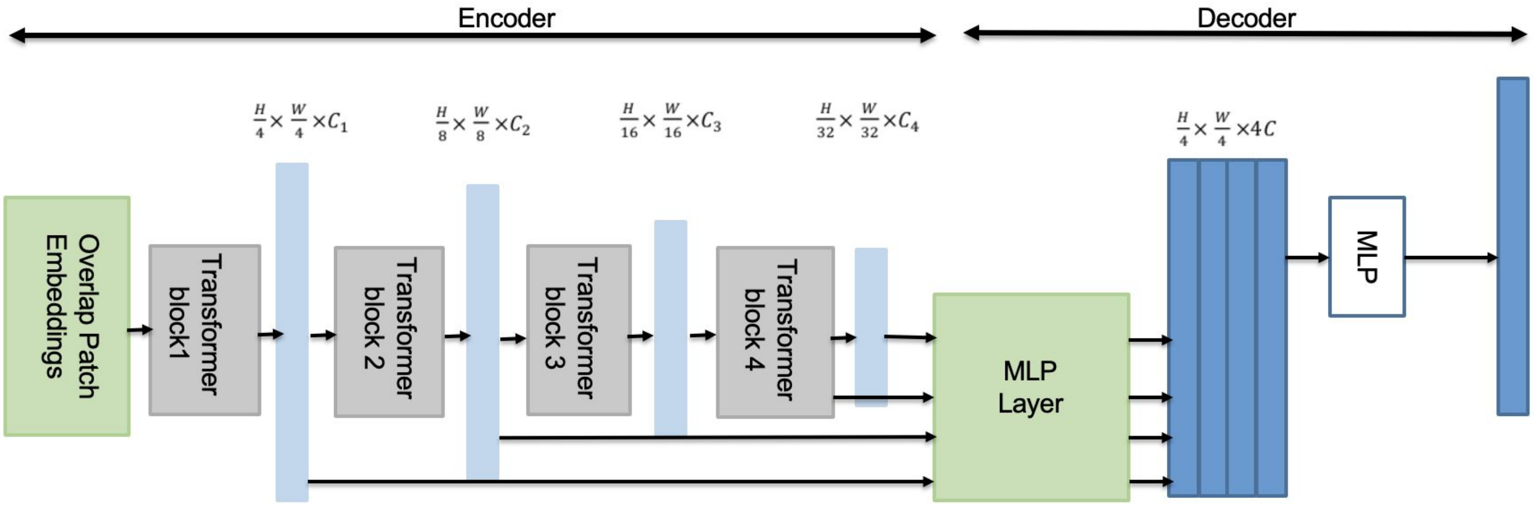
Feature Extraction

- Hierarchical **Transformer encoder** to extract coarse and fine features
- **Lightweight MLP decoder** to directly fuse these multi-level features and predict the semantic segmentation mask.



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Model

SegFormer:
Transformer Encoder +
Multilayer Perceptron Decoder

Training Set - 746 images
Testing Set - 186 images

Batch Size - 8
Learning Rate - 0.0006
Epochs - 15

Model variant	Depths	Hidden sizes	Decoder hidden size	Params (M)	ImageNet-1k Top 1
MiT-b0	[2, 2, 2, 2]	[32, 64, 160, 256]	256	3.7	70.5
MiT-b1	[2, 2, 2, 2]	[64, 128, 320, 512]	256	14.0	78.7
MiT-b2	[3, 4, 6, 3]	[64, 128, 320, 512]	768	25.4	81.6

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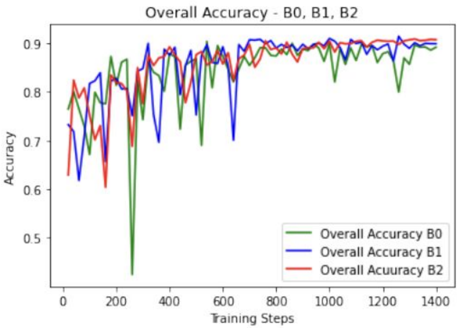
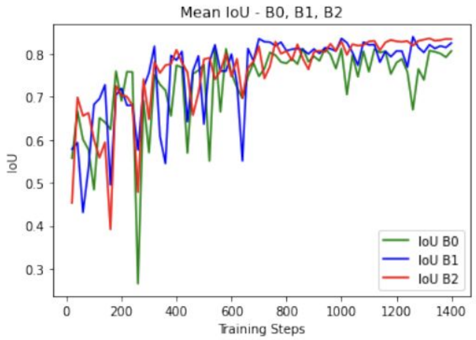
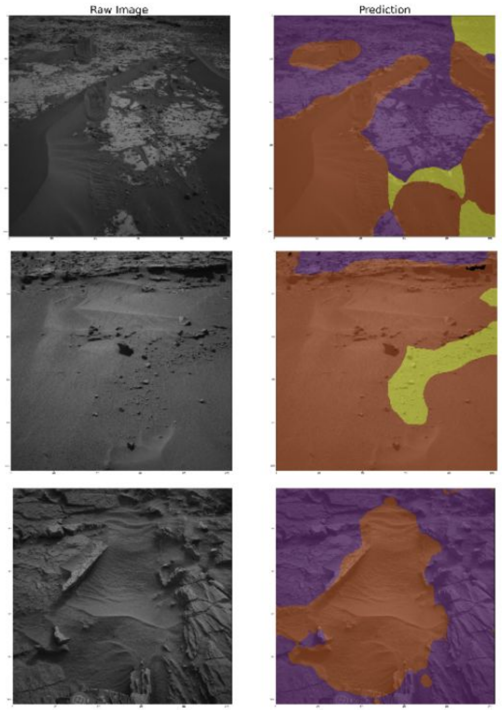
Results





Model	Mean IoU	Mean Accuracy	Overall Accuracy
SegFormer - B0	81.15%	88.61%	89.92%
SegFormer - B1	83.02%	90.33%	90.66%
SegFormer - B2	83.55%	90.75%	90.86%



Ground truth vs Prediction

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Conclusion

- Highlighting the importance of Transformers instead of employing Convolutional Neural Networks, autonomous rovers can navigate by using MultiLabel Image Segmentation for the landscape of Mars.
- It can be concluded that the segmentation process was accomplished successfully by all the three models, with SegFormer - B2 achieving the best accuracy of 90.86%.
- An upcoming scope of this project is to apply image segmentation to film captured by the rover.
- Overall, this research emphasizes the significance of autonomous navigation for rovers and presents a new method to implement for the challenging martian terrain.

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