Mars Surface Feature Extraction and Classification Using Deep Learning

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ABSTRACT

Remarkable technological achievements in the field of deep learning have led to the implementation of algorithms for surface feature identification and classification on Mars in an automated manner, consequently, this process helps to carry out the highest precision analysis with a resolution that has never been available before. CNN techniques that are based on U-Net architectures affordable to those researchers who exceedingly wish to work with competitive precision and akin to those of human experts in the identification of Martian objects. And the effect of current processes and tools on the accuracy of these detections might be discussed.To a large extent, these unexpected successes result from gathering digital terrain models (DTMs) and orbital imagery, which are the workhorse technologies that deliver critical topographic and visual data for geological surveys. Mars surface segmentation and recognition are important elements of the planning and control of the rover. Basically, it is a deterministic process for the robot to not only follow the pre-defined route but also to avoid obstacles. Still, the Martian case contains complex topography, very similar surface appearance, and a lack of numerous annotated data. These factors, therefore, pose difficult challenges to segmentation practice for the Martian surface. Hence, to bring out the information in high resolution. Mars's images are in high demand and thus many researchers work on the detection of geological structures on Mars, a geographically quite interesting planet. One of these tasks is to support mission planning and operations, such as spacecraft navigation, by making measurements that are reliable enough when it comes to the interpretation of satellite images. With the help of size variations, the image background, and orientation of certain bar-shaped landforms which are viewed from above, the process of segmenting satellite images is made difficult. Current methodologies for directed landform detection necessitate multiple pre- or post-processing steps to identify potential regions of interest and to achieve final detection results that account for orientation, which can be quite time-consuming. In this study, we propose a novel end-to-end deep learning framework designed specifically for the detection of arbitrarily oriented landforms.

1. INTRODUCTION

Space travel to extraterrestrial areas just like space has unpredicted results on the further course of humanity. Mars, which is the closest neighbor to Earth and is possibly an abode of life, has become a prime target for exploration by a multitude of countries. [3] Segmentation, identification, and understanding of Martian surface features free of the human factor, save oxygen, a critical and intrinsic step in Mars exploration campaigns. These processes are necessary to plan the route, clear the path, and position any assets. The surface segmenting correctness contributes significantly to the completion rate of actions related to Mars exploration. [8] The novel technology for this discipline is a Multi-scale Generative Adversarial U-Net (MADNet), whose utility for processing DTMs obtained from the Mars 2020 mission up to 50 cm/pixel is an example of such a method. Through this approach, interference artifacts and striping noise are thoroughly eradicated creating an appropriate background for the analysis of the small-scale structures like dune patterns, rock dispositions, and other geologic features that are needed by the global exploration of the planet. The MADNet method utilizes generative adversarial networks (GANs) to elaborate on elevation data with the aim to correctly model the geological setting, thereby this method is a useful resource for extracting surface features.

In recent years, the integration of artificial intelligence, particularly through deep learning methodologies, has significantly transformed the domains of remote sensing and planetary science. These advanced techniques facilitate the automation and expeditious analysis of extensive datasets, enabling the identification of patterns and features that may be overlooked by human analysts. Among these methodologies, semantic segmentation, defined as the pixel-wise classification of images into meaningful categories, has emerged as a potent instrument for the analysis of planetary surfaces.

The article "MarsSeg: Mars Surface Semantic Segmentation with Multi-level Extractor and Connector" authored by Li et al. (2024) marks a notable progression in this field. The authors present an innovative approach to the classification of Martian surface features, utilizing a sophisticated neural network architecture that is adept at capturing the intricate and diverse characteristics of Martian terrain.[8]

2. KEYWORDS

Mars Surface Features, Deep Learning, Convolutional Neural Networks (CNNs), U-Net Architectures, Generative Adversarial Networks (GANs), Digital Terrain Models (DTMs), Orbital

3. RELATED WORK

Several studies have applied machine learning and deep learning techniques to analyze Martian surface and subsurface features using different datasets and methodologies.

Gupta et al. [1] proposed a deep learning-based method for detecting and reconstructing subsurface discontinuities on Mars using SHARAD radargrams. A Convolutional Neural Network (CNN) was employed to filter noise and identify subsurface features like ice deposits and geological layers, with strong performance across different Martian terrains. However, the model faced challenges in weak signal detection and required region-specific training data.

Kumari et al. [2] developed a fully automated framework for mineral classification on Mars using CRISM hyperspectral data. They introduced a data augmentation technique to expand spectral datasets while using Random Forests, Support Vector Machines (SVMs), and Artificial Neural Networks (ANNs) for classification, achieving ~80% accuracy. Limitations included dependency on spectral libraries, difficulty in classifying mixed spectra, and performance variations across different terrains.

Rothrock et al. [3] introduced Soil Property and Object Classification (SPOC), a deep learning-based terrain classification system using fully convolutional neural networks (FCNNs). SPOC was applied to HiRISE and NAVCAM images, aiding Mars 2020 Rover mission planning and Curiosity Rover slip prediction. The model reduced manual effort in terrain classification but faced issues with terrain boundary misclassification and computational cost.

Mohammad et al. [4] compared semantic segmentation models (U-Net and DeepLabV3+) for Mars rover terrain classification using AI4Mars and LabelMars datasets. They employed GAN-based data augmentation, which improved classification performance by 2%. However, challenges remained in distinguishing terrain features like sand, sky, and rover hardware.

Nixon et al. [5] applied Mask R-CNN with transfer learning to extract features from planetary science datasets, identifying ice floes on Europa and clouds on Titan. Their study highlighted the benefits of onboard image processing for reducing data volume but noted low precision (30%) in Europa's ice floe detection and computational constraints.

Palafox et al. [6] introduced MarsNet, a CNN-based model for detecting Volcanic Rootless Cones (VRCs) and Transverse Aeolian Ridges (TARs) using MRO images. The study demonstrated superior performance over Support Vector Machines (SVMs) but required manual validation and additional computational resources.

Stepinski et al. [7] developed Crater Detection Algorithms (CDAs) utilizing Digital Elevation Models (DEMs) and panchromatic images for automatic impact crater detection on Mars. Their work resulted in a global catalog of 75,919 craters, significantly improving detection efficiency. However, the model struggled with degraded terrains and required manual validation for refinement.

These studies collectively demonstrate the potential of machine learning in Martian surface analysis, highlighting the strengths and limitations of different approaches in subsurface analysis, mineral classification, terrain segmentation, and geological feature detection.

4. DATA

Dataset description

The NASA Mars Reconnaissance Orbiter (MRO) used the High Resolution Imaging Science Experiment (HiRISE) camera to capture the visual and textual data of the Mars Surface Images dataset. The dataset contains around 2,000 images, secretly described, and also 70,000 one-word title printed ones. It is a well-organized dataset since it is available in both raw and processed formats with accompanying JSON data. The pictures of this dataset show variability in the size, color (including grayscale and RGB), and completeness. Some of them have missing information. Besides, the pre-processed version of the non-captioned images comes in thumbnail format (.npy), which adds to the analysis' speed. The proj is a veritable gold mine for several tasks, as the image classification, object detection, and automated captioning can be easily done with this dataset. Therefore, it is the best instrument for research not only on Mars surface features but also on planetary exploration in general.

5. MODEL IMPLEMENTATION

5.1 Data Exploration

The dataset is represented with 2,182 labeled images from 2023, which are likely observations of the Martian surface. As a first step in the analysis of the dataset, the next elements have been identified:

1. Metadata Uploads: An accompanied dataset of the source shows that besides the metadata, the captions are missing in this specific case.

2. Image Spectrum: Martian landscapes, which include posts like ridges, craters, cliffs, and dunes, are the scenery that the images depict.

3. Quality and Resolution: The pictures are clearly high-resolution ones, which means that they might have been taken by not only the HiRISE, but also the CRISM tool detailing the surface.

4. Most Possible Labels: The size and structure of the dataset gives the best basis for the assumption that the labels are classified on a terrain basis, covering also geological features, or specific surface conditions.

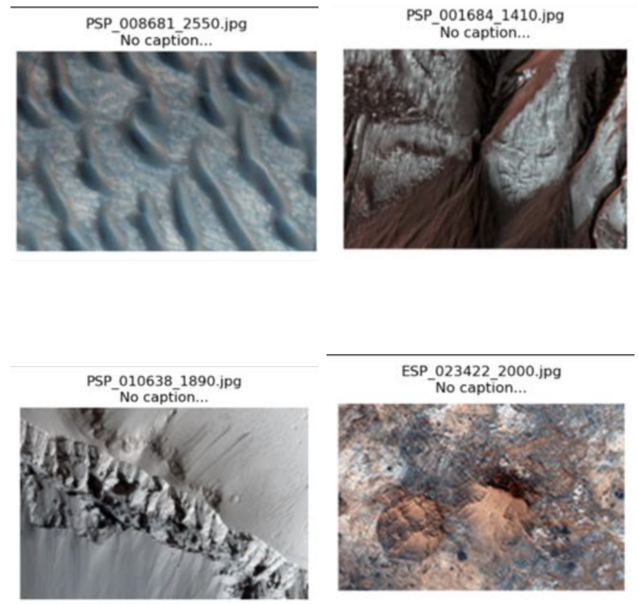

Figure 1: Images exhibit a range of Martian terrains, features such as ridges, craters, cliffs and dunes.

5.2 Pre-processing data

Images have been cleaned and resized to 512×512. Grayscale images have now been converted to RBG. Pixel values have been normalized in the range of [0,1]. Data augmentation comprised flips, rotations, and brightness.. The captioned data was split into 70% train, 15% validation, and 15% test. Non-captioned images were left for the unsupervised experiments.

5.3 Feature Extraction

U-Net which was utilized was connected to a ResNet-34 encoder, which was formerly pretrained on ImageNet. The model was trained with a combination of Dice Loss and BCE using the Adam optimizer. Latent features from the encoder were detected and plotted (K-Means, DBSCAN) to find the patterns in the unlabeled images.

5.4 Training and Test data split

We divided the described part of the dataset into three groups:Training set: one for monitoring model performance during trainingValidation set: 15% of the total for tuning and tweaking the model Test set: 15% for final evaluationThe division is in such a way that each set has different images, and at the same time, all the classes are represented equally. For perfectly unsupervised clustering, we first process the 70,000 non-captioned images separately.

5.5 Choosing the algorithm

We have chosen two distinct models that employ varying methodologies for the analysis of Martian surface imagery.

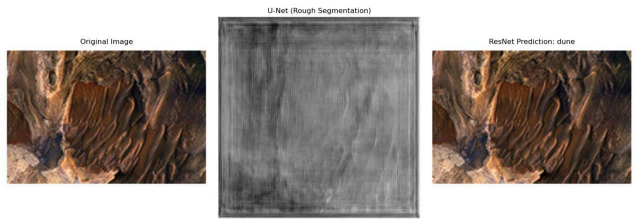

Figure 2: Visual comparison of U-Net and ResNet outputs on Mars image

The U-Net was a model used for semantic segmentation which means the technique of painting in a pixel-by-pixel manner a surface of dunes and craters. This model is characterized by its robust support, ease of implementation, and effectiveness, even with a low amount of data. Our adaptation consists of a ResNet encoder that we introduce into the U-Net to permit powerful feature extraction. On the other hand, we employ ResNet18 for image-level classification, which means the assignment of a general surface type to the entire image. Since this model is light in weight and serves as a valuable baseline for comparative analysis with more complicated segmentation models, it can be considered the lightweight one.

The idea of using SegFormer, a transformer-based segmentation model that is known in the market for state-of-the-art performance, was also explored. However, due to the additional setup complexity and time constraints, we are deferring its implementation to the final phase or future work, depending on available resources.

5.6 Evaluation metrics

To keep the evaluation process simple, we focused on: U-Net: visual inspection of segmentation masks, with plans to add IoU or Dice Score in later stages. ResNet18: label prediction accuracy across test images.

6. RESULTS (TBD)

Training is ongoing. We will report metrics like Accuracy, F1, and IoU per class. Segmentation maps and clustering visualizations will be used for qualitative analysis. A comparison with baseline methods will also be included.

7. CONCLUSION

Significant progress has been made toward achieving the project's objectives, including completing a detailed literature review and initiating dataset preprocessing and model implementation. Moving forward, we aim to complete model training and evaluation while addressing challenges related to dataset imbalance and computational resource constraints.

8. FUTURE WORK

The successful collaboration of advanced architectural methods, using Vision Transformers and Graph Neural Networks, will lead to the development of more and more complex and accurate spatial awareness technologies and, therefore, would be a specific area of research that should be focused on in the extraction and classification of surface features on Mars. The integration of the multi-modal data from sources such as HiRISE, SHARAD, and CRISM is capable of significantly improving the classification accuracy of the model. At the same time, techniques such as self-supervised learning and domain adaptation can be employed to remove the dependence on labeled datasets. The use of Generative Adversarial Networks (GANs) for the grounds of data augmentation will provide the possibility to generate the improved quality of data, hence removing the backlog from the class imbalance. Moreover, assisting the world with real-time onboard artificial intelligence will be able to significantly improve the independent navigation strengths of rovers. The creation of better solutions for subsurface detection and risk assessment will be the main thing to be done in addition to supporting the plans for the mission missions. The availability of open datasets is expected to be coupled with the interdisciplinarity of the collaboration, which is the source of the strength that allows deeper learning to be applied to planetary research and geological analysis in turn.

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