

Exploring Martian Geohazards: A Comprehensive Review of Deep Learning Techniques for Rockfall Detection and Mapping

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Abstract—The exploration of Martian terrain presents significant challenges, particularly in identifying and mitigating geohazards such as rockfalls, which pose risks to robotic missions and future human exploration. With the advent of high-resolution satellite imagery and advancements in artificial intelligence, deep learning techniques have emerged as powerful tools for automatic detection and mapping of rockfall events on Mars. This comprehensive review explores the current state-of-the-art deep learning methods employed in the analysis of Martian surface dynamics, emphasizing convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models. The study also discusses the role of transfer learning, data augmentation, and multispectral image fusion in enhancing detection accuracy under data-scarce conditions typical of extraterrestrial environments. Furthermore, the review highlights key datasets, performance metrics, and challenges such as domain adaptation and false positive reduction. This work aims to guide future research in developing robust, efficient, and interpretable deep learning frameworks tailored for planetary geohazard analysis.

Keywords—Mars, rockfall detection, Martian geohazards, deep learning, convolutional neural networks (CNNs), planetary mapping, remote sensing, transfer learning, artificial intelligence, extraterrestrial terrain analysis.

I. INTRODUCTION

Mars, often regarded as Earth's planetary neighbor and a primary target for space exploration, has attracted significant scientific interest due to its diverse surface features and geological activity. Among the many geohazards present on the Martian surface, rockfalls pose notable threats to both robotic missions and potential future human settlements. These dynamic events, characterized by the sudden detachment and downslope movement of rock material, can offer critical insights into the planet's seismic activity, slope stability, and surface evolution processes (Dingwell et al., 2020). Detecting and mapping rockfalls are essential not only for hazard assessment but also for understanding active surface processes in the absence of direct instrumentation.

The availability of high-resolution imagery from orbital missions, such as the High-Resolution Imaging Science Experiment (HiRISE) aboard NASA's Mars Reconnaissance Orbiter, has enabled the detailed observation of surface features on Mars. However, the manual identification of rockfalls in these vast datasets is both time-consuming and prone to human

error. As a solution, deep learning has emerged as a transformative approach in planetary science for automating visual data interpretation tasks. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated exceptional performance in object detection, classification, and semantic segmentation, making them suitable candidates for detecting rockfalls in complex Martian terrains (Li et al., 2021; Chen et al., 2022).

Recent studies have applied deep learning frameworks to terrestrial analogs and subsequently adapted these models to Martian datasets through transfer learning, achieving promising results in rockfall detection (Sidiropoulos et al., 2023). These methods utilize features extracted from spatial and spectral data to identify subtle changes indicative of recent geological activity. Despite the advancements, several challenges persist, including the scarcity of labeled data, variability in terrain morphology, and the need for domain adaptation to compensate for differences between Earth and Martian imagery (Zhu et al., 2020).

This review provides a comprehensive overview of deep learning techniques employed for the detection and mapping of rockfalls on Mars. It covers key architectures, preprocessing techniques, data sources, and performance evaluation metrics while identifying current limitations and future research directions. By bridging planetary geology with artificial intelligence, this work aims to advance the reliability and scalability of hazard detection systems for Martian exploration.

II. LITERATURE SURVEY

The integration of deep learning into planetary science, particularly for the detection and mapping of Martian geohazards such as rockfalls, is an evolving area of research. Over the past decade, numerous studies have demonstrated the potential of deep learning frameworks to automate the analysis of high-resolution satellite imagery, significantly enhancing the efficiency and accuracy of rockfall detection on Mars.

Early work by Bickel et al. (2019) explored manual detection methods using HiRISE imagery to identify recent rockfall events in Valles Marineris. While effective in identifying rockfalls, these approaches were labor-intensive and lacked scalability. The limitations of manual techniques highlighted the need for automation, prompting researchers to explore computer vision and machine learning techniques.

Li et al. (2021) presented one of the first studies to apply convolutional neural networks (CNNs) to Martian rockfall detection. Their model, trained on HiRISE images, achieved

high accuracy in detecting rockfall boulders and shadow patterns by leveraging spatial texture and intensity differences. They also emphasized the challenge of limited labeled datasets and advocated for transfer learning from terrestrial models.

Building upon this, Zhu et al. (2020) conducted a comprehensive review of deep learning applications in remote sensing, noting that planetary surface analysis can benefit from CNNs, recurrent neural networks (RNNs), and generative adversarial networks (GANs). Their review stressed the importance of multispectral image fusion, semantic segmentation, and the adaptation of Earth-based models to extraterrestrial data domains.

Sidiropoulos et al. (2023) implemented a transfer learning strategy using Earth-based rockfall datasets to pre-train their models and then fine-tuned them using a limited set of labeled Martian images. This approach improved the generalization capability of the model, especially in environments with minimal training data. The study achieved a high true positive rate and reduced false positives using post-classification filters.

Another promising method was introduced by Chen et al. (2022), who applied a U-Net-based deep learning architecture for the semantic segmentation of rockfall zones in Martian crater regions. The model effectively delineated rockfall paths and debris fields with pixel-level accuracy, demonstrating the benefits of encoder-decoder architectures in planetary hazard mapping.

Dingwell et al. (2020) analyzed time-lapse HiRISE images to monitor slope activity and identified thousands of new rockfall events. While their study was primarily observational, it laid the groundwork for creating time-labeled datasets essential for training supervised deep learning models. The temporal analysis of imagery provided crucial information for validating automated detection outputs.

Recent work by Kass and Baioni (2021) incorporated hybrid models combining CNNs and attention mechanisms to improve feature focus and reduce misclassification due to Martian surface variability. Their approach highlighted the significance of adaptive learning mechanisms in planetary environments characterized by noisy and unstructured data.

Despite these advancements, challenges remain. The scarcity of annotated datasets, variation in image resolution, lighting conditions, and the heterogeneity of the Martian landscape pose significant hurdles. Studies such as Zhang et al. (2021) propose semi-supervised learning and data augmentation techniques, such as image rotation, flipping, and synthetic data generation, to mitigate these challenges and enhance model robustness.

In conclusion, the literature reveals a growing interest in leveraging deep learning techniques for the automated detection and mapping of Martian rockfalls. While CNN-based models have shown the most promise, the field continues to evolve with the incorporation of hybrid models, transfer learning, and advanced segmentation architectures. Future research should focus on building larger annotated datasets, improving cross-domain adaptation, and enhancing model

explainability for safer and more reliable extraterrestrial exploration.

TABLE 1: LITERATURE REVIEW TABLE FOR PREVIOUS YEAR RESEARCH PAPER COMPARISON

S. No	Title	Author (s)	Year	Methodology	Findings	Limitation
1	Rockfall s on Mars: Detectio n from HiRISE Imagery	Bickel et al.	2019	Manual image interpret ation	Identifi ed multipl e recent rockfal ls in Valles Marine ris	Labor-intensiv e, not scalabl e
2	Deep Learnin g for Planetar y Surface Change Detectio n	Li et al.	2021	CNN on HiRISE images	Achiev ed high accurac y in detecti ng rockfal l pattern s	Limited labeled datasets
3	Deep Learnin g in Remote Sensing: A Review	Zhu et al.	2020	Review of DL models in remote sensing	Suggest ed applicability of CNNs and GANs to planeta ry analysi s	No Mars-specific impleme ntation
4	Deep Transfer Learnin g for Rockfall Detectio n	Sidiropoulos et al.	2023	Transfer learning + CNN	High TPR and reduce d false positiv es	Small Mars-labeled training sets
5	Automated Detectio n of Martian Surface Changes	Chen et al.	2022	U-Net segmenta tion model	Accurate segme ntation of rockfal l regions	Sensitiv e to image artifacts
6	Monitor ing Martian Slope Activity	Dingwell et al.	2020	Time-lapse HiRISE analysis	Observ ed thousa nds of new	Not automat ed

					rockfalls									
7	CNN-Based Object Detection in Planetary Imagery	Liu et al.	2021	YOLOv3 object detection	Detected boulders and shadow features	False positives in complex terrain	15	Rockfall Kinetics and Size Estimation on Mars	Ruesch et al.	2020	Photogrammetry + ML	Estimated size/speed of rockfalls	Limited spatial coverage	
							16	GAN-Based Image Generation for Martian Data	Kumar & Singh	2023	GAN for data augmentation	Boosted training data for rare events	Quality of synthetic images varies	
8	Rockfall Hazard Mapping Using Deep Learning	Zhang et al.	2021	Data augmentation + CNN	Improved accuracy with synthetic images	Limited generalization	17	Satellite Image Classification using Deep Belief Nets	Wu et al.	2019	DBN on multispectral images	Detected terrain changes	Shallow architecture	
							18	Change Detection using Pre- and Post-Imagery	Tanaka et al.	2020	Siamese CNN	Detected before-after rockfall events	Temporal misalignment	
9	Semantic Segmentation for Martian Terrain	Rao et al.	2020	FCN with HiRISE data	Accurate terrain feature classification	High computational cost	19	Martian Slope Dynamics: A Quantitative Study	Patel et al.	2021	Supervised ML on time-series	Analyzed frequency of rockfalls	No spatial mapping	
							20	CNN Feature Visualization in Planetary DL	Wang et al.	2022	Grad-CAM with CNN	Provided explainable results	Interpretability limited in noisy images	
10	Image Fusion Techniques in Planetary Studies	Thapa & Tang	2020	Multispectral fusion with DL	Enhanced edge detection of rockfall debris	Spectral misalignment	21	Multiscale Analysis of Rockfall Impact	Choudhary & Mehta	2022	Hybrid DL + SVM	Modelled large and small debris events	Complex pipeline	
							22	Reinforcement Learning for Martian Hazard Navigation	Yi et al.	2023	RL for robotic path planning	Avoided rockfall zones dynamically	Simulation-based only	
11	Earth-Based Rockfall Models for Mars	Kass & Baioni	2021	CNN + Attention mechanism	Improved feature focus, reduced false positives	Requires fine-tuning	23	3D Surface Reconstruction	Shankar et al.	2020	3D modeling with DL depth	Visualized hazard-prone	Data-heavy process	
							12	Learning from Imbalanced Martian Datasets	Sun et al.	2022	SMOTE + CNN	Addressed dataset imbalance	Minor performance gain	
13	Martian Geohazards and AI Detection	Amini et al.	2022	Review paper	Emphasized AI for mapping rockfall and landslides	Theoretical, lacks implementation	14	Unsupervised Learning in Martian Feature Detection	Ge et al.	2021	Autoencoder clustering	Discovered anomalies indicative of geohaz	Needs human validation	
							13	Martian Geohazards and AI Detection	Amini et al.	2022	Review paper	Emphasized AI for mapping rockfall and landslides	Theoretical, lacks implementation	

	for Mars			estimation	slopes	
24	Comparative Study of DL Models in Martian Analysis	Ahmed & Roy	2022	CNN, RNN, U-Net comparison	Found U-Net most effective	Overfitting risk on small datasets
25	Feature Extraction using ResNet for Rockfalls	Banerjee et al.	2023	ResNet-50+ classifier	High accuracy and sensitivity	Model complexity

Transfer learning allows the reuse of pretrained CNN models (e.g., VGG16, ResNet) trained on large Earth-based datasets to Mars applications, where labeled data are scarce.

Fine-tunes pretrained models for Martian terrain features

Reduces training time and improves generalization

Applications:

Earth-to-Mars model adaptation (Sidiropoulos et al., 2023)

Cross-domain feature learning (Kass & Baioni, 2021)

D. Siamese Neural Networks

These are used for change detection tasks by comparing pre- and post-event images.

Useful in detecting recent rockfalls by temporal image differencing

Applications:

Rockfall event detection using temporal HiRISE pairs (Tanaka et al., 2020)

E. Generative Adversarial Networks (GANs)

GANs are used for data augmentation and generating synthetic rockfall images to address dataset scarcity.

Helps improve model robustness and generalization

Useful for rare-event simulation in Martian datasets

Applications:

Synthetic image generation for rockfall scenarios (Kumar & Singh, 2023)

F. YOLO (You Only Look Once)

YOLO is a real-time object detection algorithm.

Detects multiple rockfall objects in a single forward pass

Balances speed and accuracy for onboard or offline analysis

Applications:

Boulder and debris detection in wide-area images (Liu et al., 2021)

G. Fully Convolutional Networks (FCNs)

FCNs extend CNNs for semantic segmentation tasks without fully connected layers.

Allows input of arbitrary image sizes

Outputs dense prediction maps for terrain classification

Applications:

III. ALGORITHMS

The detection and mapping of rockfalls on the Martian surface using deep learning involve various algorithms tailored for image classification, object detection, semantic segmentation, and domain adaptation. The primary algorithms used across recent studies are described below:

A. Convolutional Neural Networks (CNNs)

CNNs are the backbone of most deep learning approaches in remote sensing and planetary image analysis. They are used for:

Feature extraction from satellite imagery

Classification of surface anomalies (e.g., rockfalls)

Localization of object boundaries

Applications:

Detection of boulders and rockfall debris (Li et al., 2021)

High-resolution image classification (Chen et al., 2022)

B. U-Net

U-Net is a specialized CNN architecture designed for semantic segmentation, particularly in biomedical and planetary imaging.

Provides pixel-wise classification of regions (e.g., rockfall paths)

Performs well with limited datasets using data augmentation

Applications:

Rockfall region segmentation on Martian crater slopes (Chen et al., 2022)

Hazard zone mapping with boundary precision (Ahmed & Roy, 2022)

C. Transfer Learning

Martian terrain and slope classification (Rao et al., 2020)

H. Support Vector Machines (SVM) with Deep Features
Deep learning is sometimes combined with classical machine learning like SVM for post-feature classification.

Enhances classification of mixed terrain zones

Reduces false positives in post-processing

Applications:

Hybrid DL-SVM for multi-scale rockfall detection (Choudhary & Mehta, 2022)

I. Grad-CAM (Gradient-weighted Class Activation Mapping)
Grad-CAM is an explainability tool used to visualize CNN decision regions.

Helps validate predictions

Identifies key regions contributing to rockfall classification

Applications:

Model interpretability and validation (Wang et al., 2022)

J. Reinforcement Learning (RL)

Though not directly used for detection, RL is employed in navigational algorithms to avoid geohazards in autonomous rover systems.

Learns to avoid rockfall zones during exploration

Applications:

Hazard-aware rover navigation on simulated Mars terrain (Yi et al., 2023)

IV. CONCLUSION

The detection and mapping of rockfalls on Mars are critical to understanding the planet's geological activity and ensuring the safety of current and future exploratory missions. With the increasing availability of high-resolution imagery from instruments like HiRISE, traditional manual methods are no longer sufficient due to their labor-intensive nature and lack of scalability. In this context, deep learning has emerged as a powerful and transformative tool, offering automated, efficient, and accurate solutions for identifying geohazards in the Martian environment.

This review has highlighted various deep learning algorithms—such as CNNs, U-Net, YOLO, and transfer learning—that have been effectively applied to rockfall detection tasks. The integration of semantic segmentation, temporal change detection, and domain adaptation techniques has significantly improved model performance even under the constraints of limited labeled data and varying terrain conditions.

Despite notable progress, challenges remain, including dataset scarcity, false positives, and the need for better model interpretability. Addressing these limitations will require

collaborative efforts in building annotated planetary datasets, adopting hybrid learning models, and integrating domain knowledge from geoscience and space engineering.

In conclusion, deep learning offers a promising pathway to revolutionize Martian geohazard analysis, enabling more autonomous, data-driven exploration of planetary surfaces. As technology advances, the fusion of artificial intelligence with planetary science is expected to play a vital role in enhancing our understanding of Mars and supporting the future of interplanetary exploration.

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