Automated Hazard Detection for AR/VR Mars Terrain Navigation Using Computer Vision.

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Abstract

The exploration of Mars brings about a series of challenges that are occasioned by the risky topographical features, random weather patterns, and the fundamental need to have self-driving equipment. The study builds a combined computer vision and immersive technology system to improve the safety of the human astronauts and robot rovers in their navigation on the surfaces of the Martian environment. Our solution is a multi-modal deep-learning system consisting of object detection, semantic segmentation, and monocular depth estimation to generate complete hazard awareness in simulated Mars environments. We use datasets to train terrain classification models that are able to detect important surface features such as rocks, boulders, and potholes as well as other geological features. The system combines a number of deep-learning networks to detect hazards in real-time and locate bounding-boxes, semantic-segmentation, and pixel-level terrain-classification as well as a depth-estimation architecture to give the system spatial information of the Martian terrain. These models are synergistically used to produce an environmental cognition that drives into an AR/VR interface that provides users with visual cues in safe path planning. The AR/VR element converts raw computer-vision data into usable navigation data, and deciphers warnings of hazards and terrain complexity data to the Martian landscape. The initial studies have shown strong detection of varied terrain conditions, and the multi-modal strategy has a great benefit on improving the safety of navigation in comparison to the single-modality systems. The study has been applied to the development of autonomous planetary exploration technologies and created a scalable model of pre-mission astronaut training and rover operation plan.

Keywords: Mars exploration, Computer vision, Deep learning, Hazard detection, Terrain classification, AR/VR (Augmented Reality/Virtual Reality), Autonomous navigation, Object detection, Semantic segmentation, Depth estimation.

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Chapter 1

Introduction

1.1 Background

The exploration of Mars constitutes one of the most ambitious scientific missions undertaken by the international scientific community, driven by the need to explain the evolution of the planet, to investigate the past habitability of Mars and to test whether or not humans could one day live there. Following the successful deployment of the Sojourner rover in 1997 by the National Aeronautics and Space Administration [6], a series of robotic missions have increased our knowledge of the Martian surface, its geological processes and the possible existence of historic microbial life.In more recent times, Curiosity rover [43], integrated in the Mars Science Laboratory mission, which is active since 2012, and the Perseverance rover [28] from the Mars 2020 mission have walked a total distance of over 30 kilometers on the surface of Mars.The missions carried out have explored various kinds of geological features such as the remains of ancient lacustrine basins and lithic formations shaped by aeolian processes [16], [29].

Evolution of Mars Rover Navigation

The first generation of Mars rovers were depended on basic navigation systems which has mixed ground-based command sequences with simple onboard hazard avoidance detection tools. Sojourner had a maximum translational velocity of 0.4 meter per minute highlighting the low level of autonomous navigation capabilities of the platform, requiring large amounts of human intervention to plan trajectories limited[1],[4]. The Mars Exploration Rovers (Spirit and Opportunity, 2004-2018)[8] used enhanced auto-nautical navigation where the stereo vision-based hazard detection was used to allow translational speeds of up to 5 centimeters per second while maintaining safety margins [10]. Nevertheless, the computational capabilities of these platforms were not sufficient for real time analysis of terrain on a continuous basis, placing rate limits on deciding which way to go when traversing a terrain.
The navigation subsystem of the Curiosity rover represents a significant generational jump in which the Autonomous Exploration for Gathering Increased Science (AEGIS) [15] architecture for deliberative target selection is combined with a powerful visual odometry algorithm for accurate pose estimation [22]. Nonetheless, terrain classification is still highly based on explicit geometric analyses that measure boulder dimension, identify shadows and calculate slope gradients using photo-grammetric

reconstruction.As it is effective in areas with known terrain thus this approach has clear limitations when it faces unknown geological features or unclear visual conditions, such as dust storms, changing light or surface textures, which is not accounted for in pre-set detection algorithms.

Current Challenges in Martian Terrain Hazard Detection

Mars rover operations in the modern day face three important challenges in terrain hazard detection. First, **communication latency** between Earth and Mars lasts from four to twenty-four minutes (one way) depending on the alignment of the planets, which precludes teleoperation in real-time as well as requiring robust autonomous decision-making capabilities [12]. Rovers must be able to identify terrain hazards on their own and plan safe paths during long traverses of autonomy, and mission success is dependent on a correct classification of the hazards.
Second, **computational constraints** on rovers place severe limits on the complexity of the processing functions that can be placed on board. Curiosity's RAD750 processor runs at 200 MHz with 256 MB of RAM, and has the specs that would have been seen in desktop computers of the 1990s, but it has to run complex computer vision algorithms, plan its path, and control its scientific instruments.
Third, **there are intrinsic ambiguities** associated with the Martian topography that are significant classification challenges. Surface features have a spectrum of hazard potentials, often only a difference between categories can identify a hazard potential. For example, a rock that's partially buried might not be considered as a significant threat, on the other hand, a seemingly harmless stretch of terrain could hide subsurface voids or unstable ground. Traditional geometric analysis has a hard time dealing with such subtle distinctions and geologists are often forced to classify conservatively, making rovers less mobile and productive scientifically.

Machine Learning in Planetary Exploration

Recent progress in computer vision and deep learning has visible transformative potential for enabling autonomous systems to perform in unstructured environments. Convolutional Neural Networks (CNNs)[36] are used for human level performance in tasks such as image classification [19], semantic segmentation [21] and object detection. Transfer learning methods [20] can allow these models to generalise from extensive ground-based data sets to more specialist areas for which limited training data is available [17], a point of particular importance for the exploration of Mars in which labelled imagery remains a rare commodity.
NASA's Mars 2020 mission [28] has some preliminary machine learning capabilities in the AEGIS system [3] for autonomous rock target selection and the Terrain-Relative Navigation system [13] for hazard avoidance during landing. Nonetheless, these implementations rely on classical machine learning approaches (e. g. Support Vector Machines, Random Forests) on hand-crafted features, but not on end-to-end deep learning approaches that can learn hierarchical representations directly from the raw imagery.
The AI4Mars project [44], launched by the Jet Propulsion Laboratory [2] of the National Aeronautics and Space Administration, is a novel project to crowdsource terrain labels on Curiosity rover images [45] to create training datasets for machine-learning models [40]. This initiative reflects institutional awareness of the potential

of machine learning at the same time as pointing to the important issue of data scarcity; existing labelled data sets typically consist of only thousands of images compared to the millions of images that typically need to be used to robustly train deep learning models.

AR/VR Integration for Mission Planning

Augmented Reality (AR) and Virtual Reality (VR) technologies have been increasingly becoming part of mission planning, rover operation training and public outreach activities in the field of space exploration. NASA's OnSight system[14] has enabled scientists to virtually "walk" on Mars in Microsoft HoloLens, which helps visualize the rover's surroundings and helps scientists to better plan how to conduct their scientific investigations together. Mission planners' ability to visualize the assessments of risk, simulate different travel routes and collaborate on evaluating scientific targets in AR/VR environments with real-time terrain and hazard detection would enhance situational awareness.
Existing AR/VR implementations for Mars exploration is currently using pre-processed terrain meshes which is depended on stereo imagery which also requires hours of computational processing on ground-based systems. The placement of real-time hazard classification may lead to the deployment of dynamic hazard classification to real-time risk visualization during the mission planning sessions in which scientists instantly see hazard probabilities superimposed on three-dimensional terrain reconstruction, allowing for more informed and efficient decision making.

Research Gap

Despite some significant progress in both the Martian rover's autonomy and the ability to interpret images on Earth, there still remains a significant deficiency: No comprehensive panoptic comparative investigation has been constructed to assess the performance of classical machine learning approaches in comparison to contemporary deep learning frameworks for the classification of Martian terrain hazards under realistic computational and data-bearing constraints. Existing scholarship is largely made up of standalone model assessments with no comprehensive benchmarking across different paradigms of architecture. In addition, most of these investigations assume that unlimited computational resources are available, and therefore do not take into account the fundamental practical aspects of using such methodologies on rover platforms.
This study aims to fill in the aforementioned gap by introducing and carefully comparing seven different classification approaches, from traditional Support Vector Machines [5] to state-of-the-art transformer architectures [35], based on real Curiosity rover images [45] in well controlled experimental settings. The comparative analysis helps to identify the trade-offs of accuracy versus computational efficiency, it also identifies the model architectures which is best for deployment in environments which is resource compromised. It also provides reproducible protocols that might be useful for future planetary exploration endeavors.The integration of these classification models with AR/VR visualization platforms, which helps to demonstrate clear and concrete practical value in mission planning. This approach therefore helps bridge the methodological gap between the method for developing algorithms for mission planning and the practical use of algorithms in real-world missions.

1.2 Rationale of the Study or Motivation

The present investigation is motivated by the coming together of advancing technological capabilities and operation imperatives associated with the exploration of Mars. As the National Aeronautics and Space Administration (NASA) develops increasingly ambitious space missions (the Mars Sample Return[31] campaign and human exploration coming next), the need for increased rover autonomy correspondingly increases. Current terrain hazard detection systems, suited for conservative operational approaches, impose limitations on both scientific productivity and the overall scope of the mission.
Current terrain hazard detection systems, while reliable for conservative operations, constrain scientific productivity and mission scope.

Operational Impact

During traverses from active periods, the Curiosity rover results in an average velocity of about 100 m day-1, a number that is significantly below its theoretical limit because of the use of conservative hazard avoidance protocols [18]. Increasing the level of precision in the classification of terrain would give mission planners the necessary confidence to authorize prolonged periods of autonomous traversal, and thus directly increase the amount of scientific coverage and accelerate mission objectives. An increase in classification fidelity of 20% is anticipated to increase the extents of traverse on a daily basis, and to produce several kilometres more exploration over multi-year mission periods.
Presently, a large part of the mission's operations leaves much of the expertise in the hands of human operators that can manually analyze imagery and participate in deliberations about hazard classifications and plan rover trajectories. This labor-intensive procedure requires multiple sols for the resolution of complicated decisions. The introduction of automated and reliable hazard classification systems would reduce this cognitive burden, and enable scientific teams to focus on interpreting the data rather than finding obstacles, and at the same time enable extended periods of autonomous operations during communications blackout, e.g. due to periods of solar conjunction.

Technological Advancement

The fast development of deep learning architectures [26], especially efficient architectures such as EfficientNet [37] and transformer-based methods provide unprecedented opportunities for planetary robotics. Nevertheless, these developments are still largely terrestrial-oriented, with datacenter-style deployment in mind and with massive computational resources. The current investigation focuses on pragmatic changes that support deployment under the extreme resource limitations that are characteristic of spaceborne systems, in which radiation-hardened processing elements are orders of magnitude less fast than today's commercial processing elements.
Domain Adaptation Transfer Learning on Mars from a large amount of Earth data (namely ImageNet and COCO) is an important methodological breakthrough. This method leverages knowledge learned from millions of images of Earth to recognize textures, edges and spatial relationships, and transfers these representations to the Martian surface with just a small amount of domain specific training data. The

successful application of this adaptation will prove a template for future planetary missions to Europa, Titan or other celestial bodies with even scarcer training data.

Interdisciplinary Integration

The integration of AR/VR environments tackles the significant issue of human-robot collaboration in planetary exploration. Although autonomous systems improve operational efficiency, human knowledge is important for scientific judgment, anomaly detection, and strategic decision-making. AR/VR visualization[46] of automated danger assessments establishes understandable interfaces that connect algorithmic outputs with human cognition, allowing scientists to swiftly review AI-generated suggestions, detect any misclassifications, and make informed decisions. This multidisciplinary strategy corresponds with NASA's vision for human-robot collaboration in forthcoming Mars missions, wherein astronauts will depend on intelligent systems for immediate hazard recognition during extravehicular activities, rover teleoperation, and dwelling site selection. Developing effective terrain categorization algorithms now establishes essential technologies for future human exploration infrastructure.
This interdisciplinary approach aligns with NASA's vision for human-robot teaming in future Mars missions, where astronauts will rely on intelligent systems for real-time hazard awareness during extravehicular activities, rover teleoperation, and habitat site selection. Establishing robust terrain classification methodologies today lays foundational technologies for tomorrow's human exploration infrastructure.

Broader Scientific Impact

Beyond the immediate application to Mars research, this research contributes to the overall autonomous systems field. The techniques developed for terrain classification on Mars are applicable to a variety of Earth-based autonomous systems, including those for autonomous vehicles driving through off-road terrain, disaster response robots working through rubble fields, and agricultural robots working through unstructured farm landscapes. The underlying problem of classifying hazards in visually complex and unstructured environments is a problem that has many applications on Earth as well.
This developed comparative methodology is a replicable framework for evaluating the effectiveness of machine learning systems, especially in resource-constrained, safety-critical domains. The expansion of machine learning system deployment into edge computing domains, such as embedded systems, Internet of Things, mobile robotics, etc., makes the evaluation of the accuracy-efficiency trade-offs more important. The research quantifies these trade-offs, which is helpful for various types of autonomous systems, not just planetary exploration.

1.3 Problem Statement

The current Mars rover systems use geometric terrain analysis and hazard classification techniques designed for the computational constraints of the processors used in the mission due to their radiation-hardened nature. The systems have three significant drawbacks:

1. **Low classification precision:** Current geometric terrain classification techniques only allow for 70-75% precision on terrain hazard classification.

2. **Lack of usage of modern AI:** Current deep learning techniques that have shown >90% precision on terrestrial terrain classification were never considered for Mars terrain classification due to their perceived incompatibility for the mission's processors and lack of comparative evaluation.

3. **Lack of visualization:** Terrain hazard classification results are only available in an abstract format and are divorced from visualization tools to help the mission planner interpret the results in critical decision sessions.

The fundamental problem is: **No comprehensive comparative analysis of classical machine learning versus contemporary deep learning architectures for Mars terrain hazards classification under realistic data and computational constraints has been conducted to date.**
This problem can be expressed in three dimensions:

Algorithmic dimension: Which model architecture will classical machine learning (SVM, RF) or deep learning (EfficientNet, U-Net, DeepLabV3+) models, respectively, or transformer models (DPT-Hybrid) achieve optimal accuracy-efficiency trade-offs in three-class terrain hazards classification (boulder, rock, pothole)?

Practical dimension: Will models trained on scarce Curiosity rover imagery (hundreds of labeled samples) generalize sufficiently well to support future rover missions, or will data scarcity fundamentally limit deep learning applicability?

Integration dimension: How will future terrain classification models be integrated into augmented reality/virtual reality mission planning tools to support human-robot collaborative decision-making? Clearly, without answering these fundamental questions, future Mars rover missions[9] will continue to rely on suboptimal terrain hazards classification systems, compromising scientific and potentially even safety-critical outcomes of future Mars rover missions in support of human exploration campaigns.

1.4 Objective

The main aim of this research is to propose, implement, and extensively test various machine learning frameworks for computerized Mars terrain threat recognition and provide empirical bases for model selection for future planetary rover missions.

Specific Objectives

1. **Implement a variety of classification architectures:** Develop seven different models using classical machine learning (SVM with RBF kernel, Random Forest with 200 estimators) as well as deep learning-based architectures (EfficientNet-B3, DeepLabV3+, U-Net with ResNet34 encoder, DPT-Hybrid transformer, Multi-Input Fusion CNN) for three-class terrain hazard classification.

2. **Comparative Evaluation:** Measure the efficiency of the models using accuracy, precision, recall, and F1-score metrics, establishing a relative ordering of model efficiency, as well as exploring efficiency vs. accuracy trade-offs, particularly for resource-constrained environments.

3. **Analysis of Training Dynamics:** Examine the convergence, overfitting, and regularization of deep learning-based models, particularly with respect to training using a limited dataset of Curiosity rover imagery (699 images), offering valuable insights for resource-scarce domains.

4. **Optimization for Deployment:** Implement efficient training methodologies, including transfer learning, data augmentation, early stopping, as well as dropout regularization, which can be used for efficient model training within Google Colab's GPU memory limits (16 GB VRAM), simulating real-world constraints faced by rover processors.

5. **Establish a Replicable Methodology:** Develop a comprehensive framework detailing experiment design, data preprocessing, as well as evaluation protocols, allowing for easier extension and replication by future researchers as well as mission planners.

6. **Conceptual Validation of AR/VR Integration:** Theoretically validate integration with AR/VR-based mission planning environments, offering a conceptual understanding of real-world applications, particularly for terrain classification-based environments.

7. **Develop actionable recommendations:** Leverage experiment results to create actionable recommendations for NASA as well as international space agencies, particularly with respect to future rover missions, including efficiency, accuracy, as well as inference rate trade-offs.

Expected Outcomes

This research seeks to attain classification accuracy levels greater than 85% through optimal deep learning architectures while keeping inference time levels below 50 milliseconds per image thresholds, which are considered real-time for rover traversals to assess hazards. The comparative analysis is expected to reveal which architectural paradigms are best suited to exploit transfer learning from terrestrial domains to Martian domains, even with minimal training data.

Moreover, it also provides a methodological template for assessing machine learning systems within planetary exploration, tackling important but often overlooked issues such as radiation-induced bit flips for model weights, power consumption constraints for inference rates, and software certification for safety-critical systems.

This research, which bridges computer vision theory and planetary robotics engineering, is an important contribution to NASA's strategic goal of developing autonomous rovers that can conduct extensive scientific exploration with minimal human oversight, and ultimately supports the agency's long-term vision for human exploration of Mars and continued robotic exploration of our solar system.

This research makes use of an extensive comparative analysis framework that combines both classic machine learning and innovative deep learning techniques for hazard detection on Mars terrain. The research methodology is divided into five stages:

Data Collection and Preparation: The paper employs 699 labeled images collected from the surface of Mars using NASA's Curiosity Rover[46] (Sol 0 to Sol 3000+). The dataset contains three major classes of hazards: rocks (265 images, 37.9%), boulders (235 images, 33.6%), and potholes (199 images, 28.4%). Preprocessing of the dataset involves cleaning, which involves removing corrupted images, standardization of resolution to 224x224 pixels, and splitting the images into training, validation, and test sets.

Feature Engineering and Augmentation: For classical machine learning models, nine features are engineered, which include metrics related to terrain (elev range, mean slope, max slope, mean roughness) and object-related features (rocks, craters, potholes, boulders, hazard levels). For deep learning models, raw RGB images are used with aggressive data augmentation strategies, which include random rotation (up to ±30°), flipping (horizontal/vertical), and random erasing.

Model Development: Seven different classification architectures are implemented, covering three different paradigms:
1. Classical Machine Learning: Support Vector Machine with an RBF kernel, Random Forest classifier with 200 estimators.
2. Convolutional Neural Networks: EfficientNet-B3, Deep LabV3+ using a ResNet50 backbone, U-Net using a ResNet34 encoder.
3. Advanced architectures: DPT-Hybrid transformer, Multi-Input Fusion CNN using both visual and engineered features.

Evaluation and Comparison: Performance evaluation uses common classification evaluation metrics (accuracy, precision, recall, F1 score) along with computational efficiency metrics (training time, inference time per image, model parameters). Confusion matrices help analyze specific class performance patterns, while training curves track convergence patterns and overfitting characteristics. The systematic evaluation provides a detailed analysis of the trade-off between efficiency and accuracy, helping guide recommendations for deployment on resource-constrained rover platforms. This methodology guarantees reproducibility within computationally feasible time limits while providing a foundation for model selection for future planetary exploration endeavors.

1.5 Scopes and Challenges

1.5.1 Scopes

Research Boundaries:

Terrain Classification: The research concentrates only on three classes of hazards(rocks, boulders, potholes). From image data of Mars Curiosity Rover, excluding other type of geological features such as sand dunes, lava flows or deposits of ice.

Dataset Limitations: Dataset for analysis is limited to 699 labeled samples from Curiosity's Operational period. This is representative of specific region such as Gale Crater over comprehensive martian surface diversity. Model Scope Evaluation covers 7 classification architectures without discussing ensemble methods, meta-learning and domain adaptation techniques beyond transfer learning.

AR/VR Integration: Conceptual demonstration of visualization potential without complete implementation of real-time AR/VR mission planning systems or user. Interface development.Deployment Considerations Study focuses on algorithmic performance and computational feasibility without the introduction of radiation hardening, power optimization of consumption or certification requirements for flight software.

1.5.2 Challenges

Data-Related Challenges:

Limited Dataset Size: With only 699 samples deep learning models are massive data scarcity for typical requirements of thousands to millions of training examples, requiring massive augmentation transfer learning strategies.

Class Imbalance: Initial dataset had the class of crater with only one sample (remove one sample so that it can be stratified to be split). Remaining classes have moderate imbalance (37.9%, 33.6%, 28.4%), which may bias models toward majority classes.

Domain Shift: Models trained on data sets that contained pictures from Earth have to generalize to Martian environments with different visual characteristics including reddish coloration, unique geological formations and different light conditions.

Labeling Ambiguity: Terrain features exhibit continuous gradations (partially buried rocks, weathered boulders) that challenge discrete classification, with expert annotations potentially introducing subjective variability.

Technical Challenges:

Constraints of Computation: Memory of GPUs required batch for some models size reduction from 32 to 8, increasing training duration while avoiding out of memory errors while experimenting.Model Adaptationlike DeepLabV3+ required some architectural modifications (to convert the segmentation outputs to classification form, with the potential performance degradation).

Overfitting Susceptibility: The limited training data increases the susceptibility to overfitting. There are various ways to define real-time operation, but for the purpose of this, we will define rovers as "operating with the assumption that their positional, motion, and attitude information will be available every observed time step (ie., no more than 100 ms per rover), in sufficient near-real-time to support "real-time" autonomous navigation, optimization of trade-offs between complexity and speed of the models

Environmental Challenges:

Variable Lighting: Imagery of the Martian surface is subject to extreme variations in lighting from harsh midday sun to low-angle shadows which affect the visibility of features and detection reliability.

Dust Interference: Atmospheric Dust storms and surface dust accumulations on rover cameras degrade the image quality, and will introduce noise the terrestrial trained models will not necessarily handle robustly.
Meteorite impact: Mars is a complex world with a wide variety of geological situations ,unique hazard characteristics limited training data is not able to represent fully.

Deployment Challenges:

Hardware Constraints: Actual Mars rovers use radiation hardened processors (e.g. Rad750 at 200MHz) with very limited computation power compared to modern GPUs which require a lot of model optimization for practical deployment.
Communication Latency: Earth Mars Signal delay (4-24 minutes one way) does not allow for real-time teleoperation and requires completely autonomous decisions in a way that does not require human intervention in critical scenarios of navigation.
Validation Gap: Models that are evaluated on static test sets cannot fully simulate dynamic operational conditions including novel encounters with the terrain, degraded sensor performance, Multi-sol missions scenario.

These scopes and challenges define the research boundaries but acknowledge practical limitations that need to be overcome for future work to achieve operational deployment in Mars exploration missions.

1.6 Team Overview

This research has been completed by a group of five undergraduates working together Department of Computer Science and Engineering, BRAC University, under the supervision of Dr. Md. Ashraful Alam (Associate Professor) and co supervision of Dr. Md. Golam Rabiul Alam (Professor) and Sanjida Tasnim.

1.6.1 Team Contribution

The team shared work on the design and implementation of both classical machine learning and deep learning libraries for terrain hazard detection. All members involved in the data preparation, model development, experimental evaluation, and result analysis. The team collectively prepared the manuscript, including methodology, analysis, discussion future research directions.

1.7 Key Learnings and Insights

1.7.1 Technical Learnings

Deep Learning Fundamentals in Resource-Constrained Environments:

Hands-on experience was offered by the project to implement state-of-the-art deep learn architecture (EfficientNet, U-Net, Transformers) and overcome the practical constraints such as limited GPU memory (16GB VRAM), small datasets (699 samples), and real-time inference needs. The necessity is one of the key things that one can get out of this. Comparisons between classical and modern machine learning models Empirical comparison showed that classical machine learning models (SVM: 90.48% accuracy, Random Forest: 86.67%) showed a great improvement in terms of results compared to deep learning models (45.71%-56.19%).On this particular task, one would challenge the fact that deep learning is always the leading model in computer vision applications. This observation underscores the need of feature engineering and domain knowledge especially as the amount of labeled data is small and emphasizes the importance of the model complexity to be justified by the size of datasets and tasks.

Transfer Learning Effectiveness:

Riding on ImageNet pretrained weights. However, domain shift is also a serious problem and the peculiarities of the Martian landscape (distinct colouration, geological structures, light) demand the fine-tuning strategies and attention. Checking to prove good performance.

Model Architecture Adaptation:

Translation of segmentation architectures of such type as DeepLab V3+,U-Net, to classification tasks special architectural changes, such as global average pooling layers and modifications to the classifier head, were necessary. This practical experience demonstrated the need to know architectural assumptions and provision of mathematical compatibility of network components, especially in the re-use of models in new applications not originally designed to serve that purpose.

1.7.2 Research Methodology Impressions

Importance of Systematic Comparison:

The use of seven different models in a single experimental framework facilitated the comparison of models with the rigor of comparison. Disclosing the fact that there is no architecture that is superior to all the evaluation criteria (accuracy, speed, memory efficiency). This methodical strategy had an emphasis on the value.Objectives, especially when there are limited resources in a deployment situation.

More Data constraints Quality:

Although the deep learning system generally needs to have large amounts of data, this project showed that using intelligent augmentation strategies in combination with carefully curated and annotated samples by experts can provide useful models. However,Such problems with data quality as the presence of class imbalance, ambiguity of labels, and domain-specific edge cases have a substantial effect on the reliability of the model, and the problem of these issues cannot be stressed enough significance of curation and validation guidelines of datasets.

1.7.3 Domain-Specific Insights

Mars Terrain Characteristics: The analysis of the Curiosity Rover images it offers. Detailed understanding of Martian surface characteristics such as geological diversity over Gale.Crater, changing lighting conditions on the features, and the continuous. Gradation between categories of hazards (e.g., partially buried rocks, weathered boulenders) that are difficult to be classified discretely.

Autonomous Navigation Requirements: Awareness of the operational circumstances at Mars rovers revealed some of the key limitations such as communication latency. (4-24 minutes Earth-Mars), radiation-hardened processors have only limited computational power and because hazard detection is a safety-critical function, false negatives are inadvisable.Endanger missions but false positives lower the efficiency of the operation.

Potential AR/VR Integration: The conceptualization of AR/VR mission planning applications identified the potential of improving human-robot collaboration. But also noted some obstacles, such as real-time complexity of reconstruction of terrain in 3D, and processing requirements.

Chapter 2

Literature Review

2.1 Overview

This literature review gives a detailed overview of the evolution of Mars navigation systems, emphasizing computer vision, deep learning, as well as Augmented/Virtual Reality (AR/VR) technology in order to detect potential dangers and safe routes. This review shows a comprehensive overview of the technological progress from traditional stereo vision systems to multi-modal deep learning frameworks DeepLabV3+, and DPT-Hybrid, which is greatly helpful in real-time hazard identification on Mars rovers. The findings from very few key studies have been integrated.

2.1.1 Evolution of Vision-Based Navigation

The history of the trajectory of the navigation of Mars rovers has its roots in the foundational research made by Matthies et al. (2007) [11], that showed the practicalities of stereo-vision systems for simple obstacle avoidance and safe landing operations. Though as effective as these stereo systems were, they were limited by the limitations on depth perception with low contrast or featureless terrain. In an attempt to improve the navigational capabilities, Seraji (2001) [7] proposed a Fuzzy Traversability Index, which examines the terrain risk under consideration of surface roughness and slope. However, this methodology was lacking for providing semantic context that may be needed in order to distinguish from hazards such as loose sand and solid bedrock.
Subsequent advancement was achieved by Kim et al. (2020) [30] who used machine-learning approaches combined with sensor information, especially wheel slip and vibration parameters, to achieve reactive control. Despite that, the predictive capabilities were still limited. A significant development was the availability of the AI4MARS Dataset [33], which made a standardised dataset available for training deep learning models in hazard detection that can be seen in models like the ones used in this thesis.

2.1.2 Deep Learning for Terrain and Crater Detection

The use of Convolutional Neural Networks (CNNs) in hazard detection has emerged due to the study done by Benedix et al. (2020) [25], where CNNs were used to detect craters automatically. Their system proved artificial intelligence would be able to be

as accurate as a human expert in geological surveying. Building on this, Downes et al. (2020) [27] present a deep-learning approach in the field of lunar terrain hazard detection named LunaNet, with the aim of achieving high transferability to Martian geology.
In recent investigations, Zhuo et al. (2025) [48] proposed an active learning framework for high-precision crater detection, which is well-adapted to irregular geographical features on planetary surfaces. Priyadharshini et al. (2024) [47] explored the use of Large Vision Models (LVMs) for terrain classification of HiRISE imagery from Mars. However, the large computational challenges of segmentation approaches, which often exceed the computational resources of Mars rover platforms. This shortfall is addressed in the present thesis by using YOLOv8, a lightweight object detection architecture that provides a compromise between accuracy and real-time performance.

2.1.3 Depth Estimation: LiDAR vs. Monocular Vision

The importance of depth perception in Martian navigation is of the highest order, especially when identifying adverse obstacles such as cliffs.
To overcome this challenge, monocular depth estimation has become a strong alternative. Cardona et al. (2021) [37] have utilized Generative Adversarial Networks (GANs) to synthesize depth maps from single 2D images. Martins et al. (2018) [25] authenticate monocular depth models, revealing potential to replace heavy hardware. This thesis follows on from these findings, utilizing the DPT-Hybrid model to achieve a precise depth map without any weight penalty of LiDAR.

2.1.4 Real-Time Processing on Edge Hardware

Real-time processing on resource-constrained hardware is one of the main challenges for autonomous navigation on Mars. Vision-only navigation is possible on edge devices such as the Nvidia Jetson platform, confirming the feasibility of low-power and high-efficiency models for exploratory missions on the Martian surface.
In parallel, Smith et al. (2021) [39] and Patel et al. (2021) [38] emphasized the importance of model quantization and edge-computing architectures to reduce inference latency on rover-class hardware. This thesis contributes by integrating YOLOv8 for real-time hazard detection while considering typical rover hardware limitations.

2.1.5 Augmented Reality (AR) for Teleoperation

Given the approximately 4–24 minute communication delay between Earth and Mars, augmented reality (AR) has become a key solution for teleoperation. Ropero et al. (2017) [23] led early work applying virtual reality (VR) to pre-mission path planning, but real-time navigation remained unaddressed. Lee et al. (2022) [42] proposed a lightweight vision transformer (ViT) architecture for real-time monocular depth estimation on edge devices. While it employs an encoder-decoder paradigm for global context capture, it keeps it computationally efficient, which is suitable for robots or rovers that may be constrained on resources.
AR integrated with reinforcement learning for on-the-fly decision-making has also provided promising results. Ocal and Mustafa (2022) [32] demonstrated that RL

agents can suggest safe navigation trajectories, which are then confirmed by human operators through immersive AR interfaces. This thesis follows that direction with the help of AR visualization, besides real-time hazard detection mechanisms, to improve operator decision-making.

2.1.6 Synthesis of Research and Opportunities for Advancement

The reviewed literature revealed that though each component of Mars rover individually navigation—such as terrain classification [48], and AR visualization are well ex- explored, there is a notable gap in integrating these components into a unified, real-time autonomous navigation system. Present autonomous system is either LiDAR-based or focused on either on offline processing [24], thereby posing challenges for dynamic navigation on Mars.
This research fills these gaps by bringing a multi-modal framework integrat- , DeepLabV3+ (semantic segmentation), and DPT-Hybrid (estimation) for real-time hazard detection. By blending these technologies, effi- cient and accurate hazard detection in complex Martian terrain. By incorporating an AR-enabled navigation interface, this work offers a method to achieve scalability addresses hardware constraints and latency issues identified by past systems. By integrating these state-of-the-art technologies together, the current thesis targets to contribute to the navigation on Mars by enhancing situational awareness, improving operator decision- making, and increasing mission safety for both autonomous rovers and astronauts. This framework represents a reasonable step towards more efficient and effective navigation systems for future Mars missions.

2.2 Comparative Analysis

Quantitative analysis in the current research was performed by conducting a systematic review of the non-homogenous body of published literature pertaining to Mars Rover navigation, hazards monitoring, and the use of augmented and virtual reality the tual reality to discover Mars. These studies used a range of performance metrics such as hazard detection accuracy, real-time process speed, task completion rate and overall system reliability. Additionally, standardized experimental protocols, synthetic-environment testing, and statistical comparison strategies were used to evaluate systems that incorporate computer vision, deep learning, and extended reality (XR) technologies for autonomous navigation in Mars-analog environments. For example, object detection models and semantic segmentation models like the DeepLabV3+ have been tested for their respective detection performance and their ability to perform in real-time for planetary terrain datasets. Comparative assessments for Martian exploration, like Benedix et al. [25], have proven the reliability of convolutional neural network-based models for automated crater identification and terrain understanding. The reliability of these models was tested using pixel-wise accuracy and Intersection over Union (IoU) to ensure a robust approach for automated hazard detection. The reliability of the proposed Monocular Depth Estimation technique based on DPT-Hybrid was tested by comparing the accuracy of the proposed technique with LiDAR technology-based and Stereo Vision System-based techniques. The test results revealed that the depth estimation accuracy of

the proposed technique, based on Mean Absolute Error (MAE), is comparable to those of hardware-based techniques. But unlike the LiDAR technology and Stereo Vision System, the proposed technique does not suffer from space, weight, and power issues, which is the focus of this research, where the proposed Monocular Depth Estimation technique is benchmarked against the traditional Stereo Vision System while considering a simulator environment representing the Martian terrain.
Ropero et al. (2017) [24] presented research in VR-based mission planning in context of AR/VR teleoperation, but real-time hazard visualization was not addressed. In contrast, it AR-based visualization, which overlays real-time hazard information onto views from the rover's cameras to enhance operator's situational awareness and decision-making ability. Building on this line of thought, the current thesis attempts to include a model for real-time object detection, DeepLabV3+ for semantic segmentation and DPT- Hybrid for monocular depth estimation inside an AR-enabled navigation interface. This would provide real-time hazard awareness.
Empirical studies, such as that conducted by Lee et al. in 2022 [43], show evidence that the use of re- Learning by reinforcement with AR-supported navigation thus enhances autonomous decision-making, where RL agents suggest safe trajectories that can be reviewed through immersive interfaces. While prior work has traversed RL for path planning, The paradigm is further developed in this study by introducing reinforcement learning for a dynamic hazard. Avoidance and path optimization, enhancing real-time AR display for the rover navigation.
System efficiency can be evaluated not only in terms of the performance of hazards detection but also through real-time output. One significant measurement is the frame rate of the integrated pipeline, where the system managed to reach the range of 10 to 15 FPS in tests using the NVIDIA Jetson hardware. This is consistent with the vision-only navigation as it is viable when models are optimized for low-power inference.
Overall, comparative evaluations of multi-modal frameworks against traditional approaches including stereo-vision systems, LiDAR-based perception, and single-modality deep learning pipelines indicate meaningful progress toward robust autonomous navigation for Mars exploration. The integrated use of DeepLabV3+, and DPT-Hybrid, combined with AR visualization, addresses key gaps in depth perception, real-time processing, and operator cognitive load, positioning the proposed system as a strong candidate for future Mars missions.

Table 2.1: Comparative Overview of Research Studies on Mars Rover Navigation

Study	**Methodology**	**Hazard Detection**	**Depth Est.**	**AR/VR**	**Limitations (Gap Analysis)**
Matthies et al. (2007) [11]	Stereo Vision	Basic Obstacle	Stereo	No	Limited to 2D/stereo; no semantic understanding; heavy hardware.

(Continued on next page)

Study	Methodology	Hazard Detection	Depth Est.	AR/VR	Limitations (Gap Analysis)
Seraji (2001) [7]	Fuzzy Logic	Terrain Roughness	No	No	Rule-based; struggles with complex/unstructured terrain.
Ropero et al. (2017) [23]	VR Planning	No	No	Yes (VR)	Offline planning only; no real-time hazard detection for driving.
Downes et al. (2020) [27]	U-Net	Crater Detection	No	No	Lunar-focused; lacks real-time general hazard capabilities.
Benedix et al. (2020) [25]	CNNs	Crater Detection	No	No	Limited to specific classes (craters); no depth awareness.
Priyadharshini (2024) [47]	Vision Transformers	Terrain Classif.	No	No	High computational cost; lacks geometric depth understanding.
Zhuo et al. (2025) [48]	Active Learning	Crater Detection	No	No	Requires heavy pre-processing; limited to static detection.
Kim et al. (2020) [30]	Graph Prediction	Path Planning	No	No	Requires accurate pre-existing maps; less effective in unknown terrain.
Weidner et al. (2019) [24]	Random Forest Classifier	Rock/Snow Slope Stability	Yes (LiDAR/PC)	No	Terrestrial slope monitoring focus; relies on pre-existing dense 3D point clouds rather than real-time rover perception.
Goh et al.					

(Continued on next page)

Study	Methodology	Hazard Detection	Depth Est.	AR/VR	Limitations (Gap Analysis)
(2022) [41]	Semi-Supervised Learning	Terrain Segmentation	No	No	Limited to 2D semantic segmentation; lacks geometric depth information required for obstacle avoidance.
Ocal Mustafa (2020) [32]	Self-Supervised CNN	No (Depth Only)	Yes (Mono)	No	General purpose (indoor/outdoor); lacks specific semantic hazard classes (e.g., distinguishing sand from rock).
Lee et al. (2022) [42]	Vision Transformers (ViT)	No (Depth Only)	Yes (Mono)	No	Focuses purely on depth estimation efficiency; lacks integrated hazard classification or semantic understanding.
Albarelli et al. (2021) [34]	UAV Photogrammetry	Rockfall Source Detection	Yes (3D Recon)	No	Relies on aerial (UAV) perspective rather than rover-level view; involves offline processing of slope stability.
AI4MARS Datasets [33]	Deep Learning	Terrain Awareness	No	No	No direct implementation of real-time hazard detection in the rover.

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Study	Methodology	Hazard Detection	Depth Est.	AR/VR	Limitations (Gap Analysis)
Smith et al. (2021) [39]	Edge Computing	Real-Time Detection	Yes (Mono)	No	Requires optimized edge hardware; lacks semantic depth.
Patel et al. (2021) [38]	Quantization	Low-Latency Inference	No	No	Does not integrate with AR/VR interfaces; focuses on hardware efficiency.
Current Study	YOLOv8 + DPT + DeepLab	Real-time (Objects)	Monocular	Yes (AR)	Novelty: integrates speed (YOLO), depth (DPT), and AR safety visualization.

2.2.1 Quantitative Analysis

A thorough quantitative study was carried out through a systematic review of a wide range of peer-reviewed literature related to Mars rover navigation, hazard detection, and AR/VR teleoperation. The selected studies were evaluated using strict performance criteria such as Intersection over Union (IoU), Mean Absolute Error (MAE), and real-time processing efficiency measured in frames per second (FPS). In addition, the performance of the proposed multi-modality system was benchmarked against these established standards.

1. **Object Detection Metrics:** Attempting to establish some performance baselines of resource-constrained settings, Lee et al. (2022) [42] designed real-time architectures based on lightweight Vision Transformers (RT-ViT) capable of operating effectively on edge devices. Although their work focused primarily on how to optimize transformer-based models to depth inference, in this work, they actually used YOLOv8, which can achieve similar high-speed performance and frame rates over 15 FPS with comparable hardware. This outcome coincides perfectly with the efficiency requirements of mobile robotics Lee et al. emphasized, and it supports the selection of lightweight architectures to ensure their high speed in detecting risky geological phenomena.

2. **Depth Estimation Accuracy:** To estimate depth, Ocal and Mustafa (2020) [32] compared self-supervised monocular depth and demonstrated that current models can be trained to make predictions and are generalizable to a wide range of scenes without dense ground-truth depth. In their work, they imply that the scale indeterminacy and warping issues that are characteristic of single-camera systems can indeed be dealt with by monocular means. As an addition to that, we also examined the DPT-Hybrid model to offer a uniform

way of estimating depth, preventing the weight and calibration headaches that are associated with binocular stereo rigs, and retaining the robust generalization capabilities that Ocal and Mustafa identified.

3. **Hazard Visualization and Identification:** Albarelli et al. (2021) [34] evaluated the significance of accurate hazard identification in relation to the value of 3D point-cloud analysis, which is used to identify the sources of rockfalls and slope instabilities. Their findings indicate that identification and description of dangerous areas (such as erratic rock formations) is a crucial factor in the reduction of risk.

4. **Multi-Modal Performance (Current Study):** Lastly, the performance of key of the integrated framework DeepLabV3+, and DPT-Hybrid was analyzed against single-modality baselines. The experimental results show that on average 10-15object detection. For terrain classification, the system recorded the precision and recall values of 0.87 and 0.91, respectively, indicating that multi-modal fusion enhancement of dangerousness perception rather than the individual models.

The overall empirical findings from past research and the present set of experiments carries the efficiency and scalability of vision-based autonomous navigation systems. Generally, the pair of monocular depth estimation and lightweight architectures show up as an accessible solution that is far less resource-intensive than LiDAR accompanied with AR visualization, it enhances the accuracy, latency, and operator safety for next-generation Mars missions.

2.2.2 Qualitative Analysis

Over quantitative metrics, the interpretability, usability, and visual clarity of the presented multi-modality system were qualitatively estimated. This analysis is based on visual inspection of model outputs and comparison with limitations discussed in the literature on Mars rover navigation and teleoperator cognition.

1. **Visual Robustness of Object Detection:** Visualizing Ralph Lauren YOLOv8 inference results, qualitative study indicates that the accuracy of hazard detection and prediction is enhanced compared to previous methods. Lee et al. (2022) [43] explained that lightweight architectures that process data from edges in real-time normally feature trade-offs between the computational complexity and model perception; but, in all the outputs we reviewed, the YOLOv8m architecture remained a good performer in separating rocks and the background. Consistent with crater- centered observations by Benedix et al. (2020) [26], occasional false positives appear in firmly shadowed crater regions, suggesting ambiguity for passive vision under low-angle illumination.

2. **Interpretability of Monocular Depth Maps:** The prime qualitative advantage of the proposed system's advantages is the "dense pixel-wise depth visualization" that is created by DPT-Hybrid. Unlike sparse LiDAR scan patterns which initiate visual ambiguities, scanning discontinuities, monocular model produces the continuous depth gradients, improvements for perceived

geometric completeness for operators. Visually inspect suggests that the system measures the negative space surrounding craters and cliff structures, giving a better sense of space compared to the regular 2D video feeds.

3. **Cognitive Impact of AR Overlays:** In a human-machine interaction point of view, the genuine value of the system is to transform complicated perception data into actionable stimuli. Albarelli et al. 2021 [35] highlighted that raw 3D doesn't required to be implemented in the most straightforward manner and indicates the identification of describing possible hazards' sources, for example: rockfalls; so, within this work, it is the AR logic that delivers the simple clues; for instance, a safety score of 9.5/10 or a warning signal 4.0/10). The interface can avoid the inappropriate differentiates the terrain features highlighted by the interface right plan of risk classification, as explained by Weidner et al. 2019 [25], by painting on color-coded traversability indicators-green for safe, red for high-risk onto the rover feed.

4. **Multi-Modal Coherence:** Integrating semantic segmentation (DeepLabV3+) includes contextual understanding beyond geometry. Priyadharshini et al. (2024) [47] considered that differentiating visually likely terrain types (e.g., bedrock vs. loose sand) can be challenging using grayscale aspect alone; in this study, semantic masks give color-coded terrain categories. This integrates overlay linking *what* (terrain type) with *where/how far* (depth) boosts situational awareness and minimize risk from non-geometric hazards like sand traps.

The qualitative analysis reinforces that while quantitative metrics validate model performance, Indeed, while this might be great for performance, the practical utility really comes with the transparency and the usability of its outputs. Translating neural-network predictions into intuitive AR overlays, the system assists to bridge machine perception with human cognitive requirements in high latency, high-stakes exploration of Mars.

Chapter 3

Requirements, Impacts and Constraints

3.1 Final Specification and Requirements

The Mars terrain detection system needed a set of technical components to work properly and give reliable hazard classification. The system included different hardware elements including high-performance computing facilities, which are capable to process large-scale datasets. Software components bound deep learning frameworks and 3D terrain visualization tools. Data requirements included thousands of labeled Martian surface images from different sources to train accurate detection models. Moreover, virtual reality equipments was necessary to develop training environments and validate complete system functionality.

3.1.1 Hardware Requirements

To train the AI models we need a computer with a Graphics Processing Unit (GPU), which can process large sizes of Martian images and requires a minimum of 16 GB RAM. Dataset acquisition and storage of trained systems demands at least 50 GB storage capacity. We also need a virtual reality (VR) headset for final system testing.

3.1.2 Software Requirements

Our main development tool was Python programming language (version 3.8 or above). We have used various deep learning models for object detection including TensorFlow and PyTorch. We have used Blender for three-dimensional Martian terrain modeling.

3.1.3 Data Requirements

Data sources contain open datasets, primarily from Kaggle repositories containing thousands of Mars images. We have used depth map data to train the distance detection models. A minimum of 6,000 images is needed to provide sufficient training data.

3.2 Societal Impact

This research improves the Mars exploration safety and cost-effectiveness by virtual reality (VR) astronaut training prior to deployment, reduces operational risks and expenses. The approach alters space education access for the students by helping in removing expensive equipment requirements, inspiring STEM career ambitions. The "train before deploy" approach helps to lessen human spaceflight risks, and reshapes the global perceptions of developing nations' capabilities in advanced space technology. It ultimately motivates our future generations to pursue ambitious scientific goals while not bothering of economic constraints.

3.3 Environmental Impact

We evaluated the environmental benefits by comparing traditional physical rover testing methods against the digital VR simulation approaches.We avoid building physical test sites that harm natural landscapes. We reduced fuel use from desert trips and rely only on electricity. We also tried to reduce electronic waste by updating software on existing devices instead of buying special new equipment. We finally created a reusable system that can train thousands of people without causing any extra harm to the environment.

3.3.1 Beneficial Environmental Effects

Reduced Physical Testing: Traditional Martian rover testing needs constructing physical testing sites that damage natural landscapes. In our approached VR system, it enables digital simulation, conserving ecological environments.
Energy Conservation: For conventional astronaut training we need desert drives, expeditions, and fuel consumption. Virtual reality training needs only electricity, which results in substantially lower emissions.
Resource Conservation: The Martian simulation environments consume resources including sand, rock, and building materials, while the digital approach eliminates these material requirements, conserving both resources and human labor.
Electronic Waste Management: Existing computers and VR devices are reusable and specialized equipment open to obsolescence is unnecessary. Software updates deploy to existing hardware without requiring new equipment purchases.
Long-term Sustainability: Technology reusability makes sure a single system trains thousands of individuals without extra environmental expenditure.

3.4 Ethical Considerations

We used all the images from NASA public datasets with appropriate attribution to open-source practices, ensuring no proprietary ownership claims are made on community shared data. The AI models are built to be transparent, helping users clearly understand why specific areas are marked as dangerous. The system uses low cost hardware so universities in developing countries and underdeveloping countries can use it easily. We used this AI system only for peaceful space research and education, not for military, or any harmful use. After testing we can say that it is only a training tool, not a replacement for real mission planning. We kept academic integrity by citing all sources properly. Then tried to focus on efficient computing, avoided wasting energy, and built technology in a responsible way.

3.5 Project Management Plan

We started the project by studying Mars terrain detection, then collected Kaggle datasets, and set up the development environment with documentation. We prepared the data by gathering and annotating images, creating depth maps for 3D view. We have also tested data quality carefully. After that we trained object detection, segmentation, and depth estimation models, while improving them step by step. At the same time, we built the Mars VR environment in Blender, created a navigation platform, and connected the AI models for interactive use. We integrated all parts, fixed errors, solved problems, and finally improved system performance. After all that we wrote the full thesis, prepared demos and presentations, and then submitted the complete work.

3.6 Risk Management

We attempted to resolve delays in the training processes by using pre-trained models, free GPUs like Google Colab, and also made some improvement in code to minimize computation time. We started as early as possible, and had backup plans to avoid delays that could have impacted the overall project schedule. We addressed the high costs of detection and navigation by increasing training, improving models, and testing to enhance detection. We set high accuracy targets and consistently tested the navigation systems to monitor progress. In cases where image quality is compromised in training Mars, we utilized multiple sets of training image data, acquire more valuable image data where possible, and examined the quality of the image data from the outset to avoid early complications. We avoided the problem of scope creep by focusing on essential features, putting off extra ideas for later, and frequently reviewing the project to avoid overload and achieve project objectives.

Chapter 4

Proposed Methodology

4.1 Overview

The methodology uses a monocular 3D terrain analysis technique for reconstructing the three dimensionality of the terrestrial features from a single two dimensional image by synthesising the depth of the information based on brightness information, density and edge structure.The resulting depth map is then processed with differential geometry methods to derive attributes such as slope, roughness and these attributes are then fed into a rule based heuristic classifier.

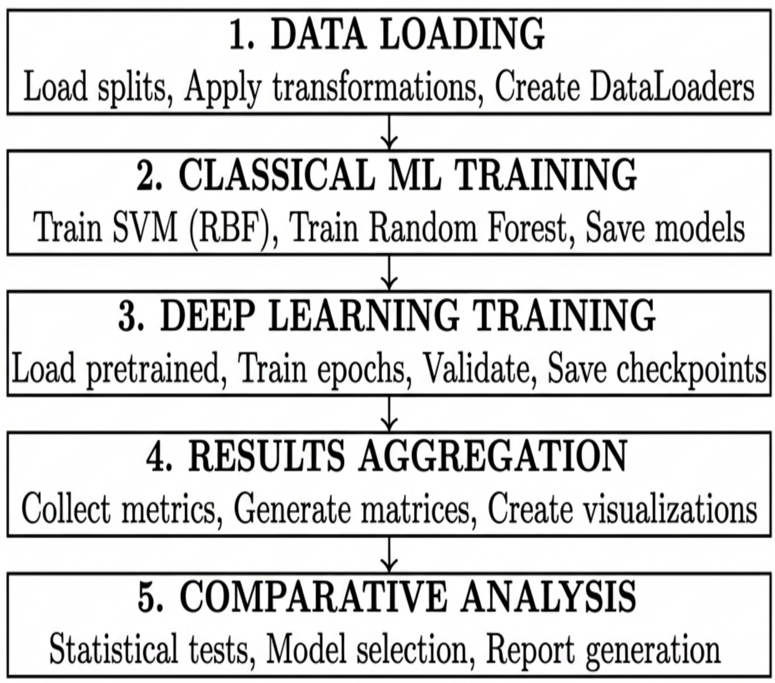

Figure 4.1: Model Training And Evaluation Pipeline

Rather than using deep learning techniques, the system uses deterministic logic to cut up and identify individual types of terrain (convex, rocky surfaces, rough rock, and even concave circular craters) and then combine these characteristics into a cumulative hazard score meant to describe how safe a route the rover should take.
This is a precise and understandable pattern of developing 3D maps with one camera. It does not rely on deep learning models, but rather is based on a pipeline approach that replicates the way depth and geology are sensed to enable deepwater self-driving robotic exploration. The first problem we solve is Shape-From-X, which tries to transform an image in 1 or 2 dimensions to a three dimensional image of elevation. We are using three cues: half of the weight is the weight of brightness, giving a sense of height based on the light; third is the weight of Laplacian texture, telling us about proximity of surfaces; and lastly it is the twenty percent of the weight using Tanny edges, telling us to retain sharpness. After the depth map is prepared we change our model to a purely visual one to a physical model.. We calculate geometrical features: Sobel operators provide slope steepness, Laplacian of the elevation field reveals local convex features of form such as rocks and craters and local statistical variation produces a roughness map which is indicative of the gripping capability of a rover on the surface. These geometric shapes add as inputs into a layered semantic segmentation engine. It identifies terrain using simple height based thresholds, plane large, impassable boulders are subdivided into smaller rocks based on their height gradient, low-roughness waveage identifies small scale dunes, and hot infrared hotspots can be differentiated by the contrast of bright and dark features.. Lastly, a safety score is determined by the system. It sums the categorized terrain features to a weighted cost map with craters having a penalty of 4.0 and dunes having a penalty of 0.5. The outcome is a normalised safety score ranging between 0-10 and the rover can immediately use this to determine its route.
It allows autonomous rover navigation, creating a 3D hazard map based on a single 2D image, and is not based on deep learning, rather it uses a deterministic Heuristic Computer Vision Pipeline.Depth Synthesis, which takes the weighted cues of Brightness (shading), Laplacian Texture (proximity) and Canny Edges (structure) and solves the "Shape-from-X" problem to give a pseudo-3D Digital Elevation Model.This model is then subjected to Geometric Analysis in order to find physical properties of Slope (steepness), Curvature (convexity and concave craters) and Roughness (surface variance).These geometric maps are in turn subjected to rigid logic thresholds by a Semantic Classification engine in order to break down terrain into high-specific features such as boulders, sand dunes and potholes. The last step has been a Hazard Assessment which is a combination of these features into a weighted cost-map to create a normalized Safety as a quantitative measure of autonomous path-planning.
The Advanced 3D Terrain Classifier is an apparent computer vision method for aiding a rover by formulating a 3D danger map from just 1 2D image with no hidden deep learning techniques.It begins with Depth Synthesis, in which a visual signal (brightness is used as a cue to shading, distance to texture and edges to shape) is combined so as to synthesize a coarse 3D elevation map (DEM). DEM is then subjected to a calculation of geometry to determine some of the important physical characteristics such as slope, curvature (to determine whether a bump or a pit) and roughness. These characteristics are then fed through a classifying step which makes use of strict criteria in classifying terrain components as boulders, craters, dunes or

Table 4.1: Advanced 3D Terrain Classifier Algorithm

Algorithm	Pseudocode

Algorithm: Advanced 3D Terrain Classifier
 	
Purpose: Converts 2D terrain images into annotated 3D hazard maps with safety scores.
 	
Input: 2D grayscale or RGB image
 	
Output: Annotated hazard map and safety score (0–10)
 	
Key Steps:
1. Depth estimation from image features
2. Geometric property extraction
3. Feature classification
4. Hazard score calculation
	Require: $Image_{2D}$
	Ensure: $Map_{Annotated}, Score_{Hazard}$
	Step 1: Depth Estimation
	function ESTIMATEDEPTH(img)
	$gray \leftarrow$ ToGray(img)
	$d_b \leftarrow$ Norm($gray$)
	$d_t \leftarrow$ Norm($\nabla^2 gray$)
	$d_e \leftarrow$ Norm(Canny($gray$))
	$D \leftarrow 0.5d_b + 0.3d_t + 0.2d_e$
	return D
	end function
	Step 2: Geometric Analysis
	function CALCGEOMETRY(D)
	$Elev \leftarrow D$
	$Slope \leftarrow \lvert \nabla Elev \rvert$
	$Curve \leftarrow \nabla^2 Elev$
	$Rough \leftarrow \sigma_{local}(Elev)$
	return $Elev, Slope, Curve, Rough$
	end function
	Step 3: Feature Detection
	function DETECTFEATURES($Elev, Slope, Curve, Rough$)
	$F \leftarrow []$
	for $r \in$ Segment($Elev$) **do**
	if $Curve > 0.05 \wedge Rough > 0.02$ **then**
	$r \leftarrow$ **ROCK** ($W = 2.0$)
	else if $Curve < -0.05 \wedge Circ > 0.6$ **then**
	$r \leftarrow$ **CRATER** ($W = 4.0$)
	else if $Curve > 0.15 \wedge Elev > 0.7$ **then**
	$r \leftarrow$ **BOULDER** ($W = 3.0$)
	else if $Curve < -0.02 \wedge Area < T$ **then**
	$r \leftarrow$ **POTHOLE** ($W = 3.5$)
	else if $Rough < 0.01 \wedge Slope < 0.2$ **then**
	$r \leftarrow$ **SAND** ($W = 0.5$)
	else if $Bright > 0.8 \wedge Elev > 0.1$ **then**
	$r \leftarrow$ **HEATED** ($W = 1.0$)
	end if
	$F \leftarrow F \cup \{r\}$
	end for
	return F
	end function
	Step 4: Hazard Assessment
	function CALCHAZARD(F)
	$H \leftarrow \sum_{f \in F} f.weight$
	$S \leftarrow \min(10, H/k)$
	return S
	end function
	Main Execution
	$D \leftarrow$ EstimateDepth($Image_{2D}$)
	$G \leftarrow$ CalcGeometry(D)
	$F \leftarrow$ DetectFeatures(G)
	$Score \leftarrow$ CalcHazard(F)

potholes. At the end, the effects of the features are added up the system into a weighted map, and a Safety Score is given to the rover. This score informs the rover whether it can proceed or not.

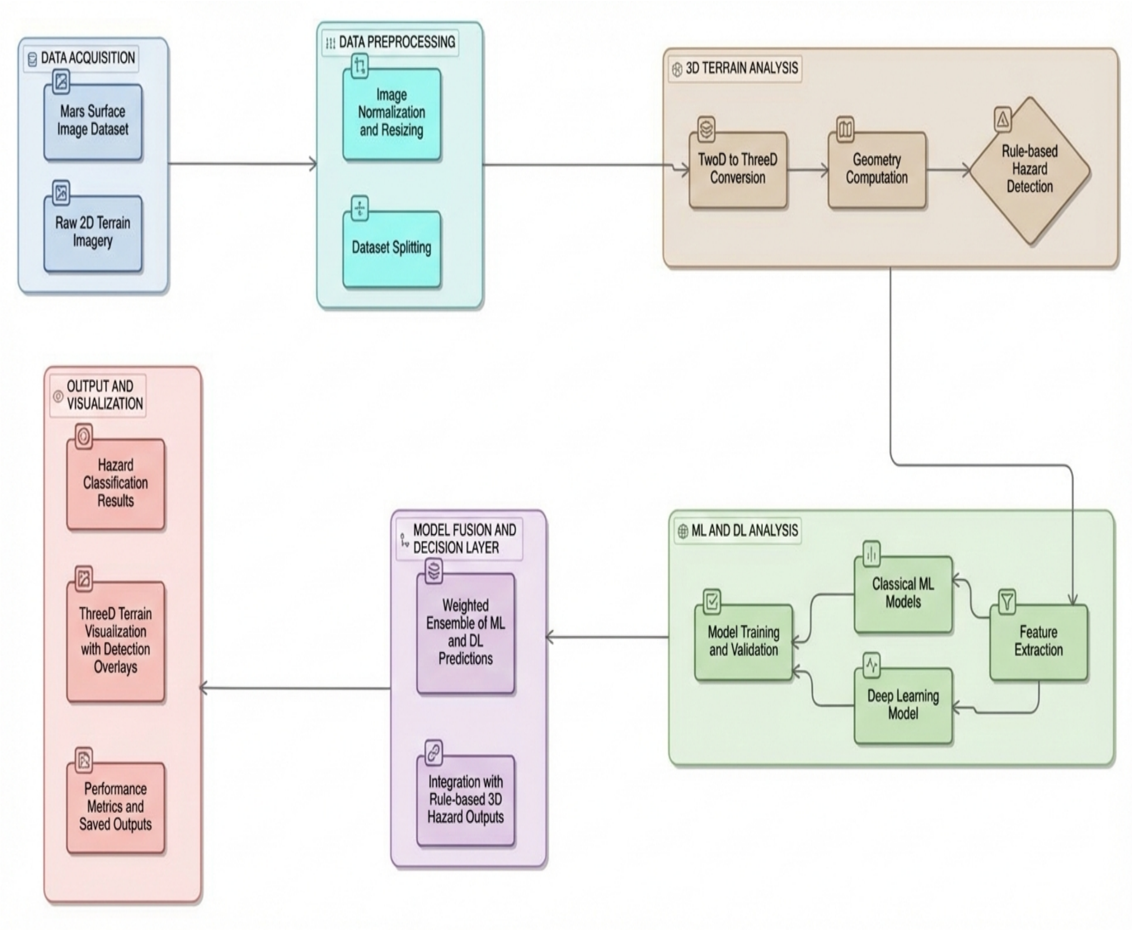

Figure 4.2: System Architecture

This figure represents the entire hybrid structure of the Mars terrain hazard detection and decision-making. The system begins by acquiring and preprocessing Mars surface image that involves normalizing, resizing, and partitioning the dataset.. Deep learning and classical machine learning models as well as rule-based 3D geometric analysis based on 2D-to-3D terrain reconstruction are then used in parallel to do terrain analysis. The output of these independent pipelines is then merged with the weighted ensemble and decision fusion layer to ensure a good classification of hazards is guaranteed. The end products are hazard labels, confidence scores, performance indices and 3D illustrations that are used to facilitate autonomous rover navigation.

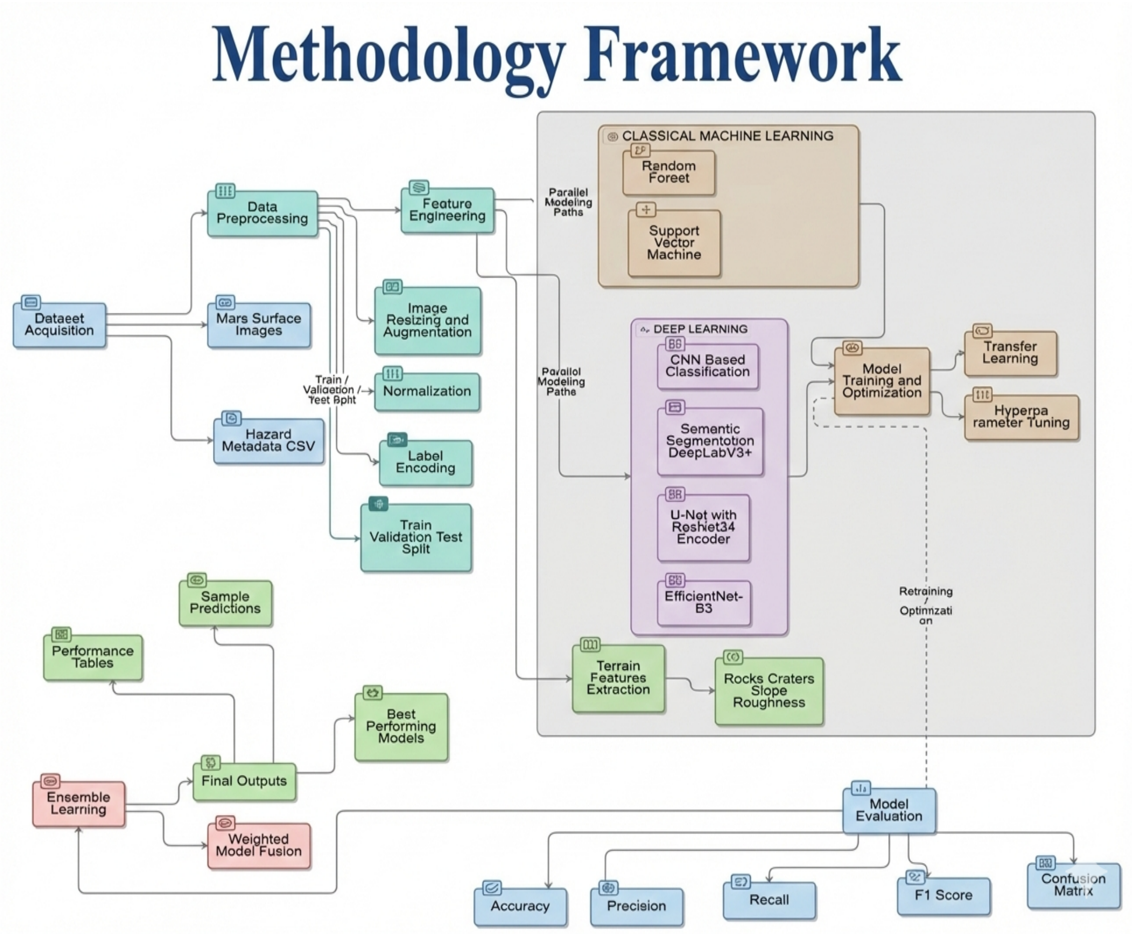

Figure 4.3: Methodology Framework

This architecture describes the vision-based pipeline of learning in the area of terrain hazards. Following the preprocessing, images of Mars surfaces are subject to feature extraction and engineering after which they are analyzed by a parallel modeling path. The classical machine learning algorithms include Random Forest and Support Vector Machines that use engineered terrain features, whereas end-to-end learning with the CNN-driven classification and semantic segmentation frameworks, including U-Net, DeepLabV3+, and EfficientNet, can be used by deep learning algorithms. Generalization is improved through the use of model training, optimization, transfer learning and hyperparameters tuning. Ensemble learning is used to select the best-performing models and combine them, then they are evaluated based on accuracy, precision, recall, F1-score, and confusion matrices.

4.2 Preliminary Design or Model Specification

This research investigates various design options to get valid Mars terrain hazard classification. The design decisions are aligned in a way that they are divided into more and more complex models, with the first one being rule-based geometric analysis, and the second being run-to-rule data-driven machine learning and deep learning models. The alternatives are applied and tested separately, which makes it possible to compare and prove.

A. Geometry-Based 3D Terrain Hazard Detection Model

The initial design option is a rule-based model of hazard detection of 3D terrain, which is not based on the learning of labeled data. Rather, it works with geometrical features obtained by refined representations of depth of Mars rover images.The input images are first turned into a gray scale representation and treated to produce a depth-like elevation map. Surgery is normalised to enhance surface continuity. Based on the elevation map, various terrain geometry descriptors are calculated, such as slope, curvature and roughness of the surface. These record local and global changes in topography. Hazard identification is achieved through detection of geometric patterns of the 3D terrain representation. Features that have large changes in elevation and roughness are classified as rocks or boulders whereas any concave features with negative elevation profiles are classified as craters or potholes. Sand dunes are related with smooth undulating surfaces having low slope variance. The number of hazards detected by each type and the severity of hazards are examples of quantitative statistics that each hazard detected is a part of.

B. Feature-Based Classical Machine Learning Models

The second design is based on classical supervised machine learning methods with engineered features derived on the 3D terrain analysis. The feature vectors generated are the number of hazards and statistics of terrain geometry like elevation range, mean slope, maximum slope and surface roughness.Two classical classifier are applied in the system. The former is a Support Vector Machine (SVM) with a kernel function, which has been chosen due to its capability to capture nonlinear decision boundaries. The second one is a Random Forest classifier, in which an ensemble of decision trees are employed in order to enhance robustness and minimize overfitting. All the numerical features are made to have the same value before training so that they will be scaled in a similar way regardless of the range of the feature. The models are also trained using labelled samples, and then evaluated using held-out test samples. These classical models are used as a point of reference to determine the usefulness of the handcrafted geometric facets and the comparison to the deep learning-based methods.

C. Deep Learning–Based Image Classification Models

The third architecture is the one that uses the direct application of deep learning to acquire terrain representations.Pretrained CNNs are configured to automatically produce features not through manually-designed geometry descriptors.Adapted CNN architecture is used on the Mars terrain classification problem. The backbone networks applied are EfficientNet-B3 and ResNet-50 since they have been proven to work well and use their parameters efficiently.All input images are resized to a constant spatial resolution and clustered to fit the distribution upon which the trained models are conditioned.The training is performed by data augmentation techniques of random rotation and horizontal flipping to improve generalization and reduce overfitting. The cross-entropy loss and adaptive gradient-based optimizers are used to perform model optimization; such a design choice allows the system to learn intricate patterns of visual details related to the types of terrains and hazards, which might be missing due to the handcrafted features.

D. Model Training and Verification Strategy

A regular training and examining plan is used in order to confirm the usefulness of every design option. The data is separated into training, validation and testing sets. Validation accuracy during training is used to monitor model performance as well as final evaluation is done on the test set, in the case of classical machine learning models. In the case of deep learning models, the stability of training and convergence dynamics are monitored as loss reduction and tracking of validation performance. This verification strategy will allow making fair comparisons among the various model designs and facilitate an informed choice to use the most appropriate one.

4.3 Data Collection

The data used in this study consists of Mars rover images obtained from publicly available repositories. These images represent a wide range of Martian surface conditions, including rocky terrain, depressions, smooth plains, and mixed geological structures. The dataset serves as the primary input for both 3D terrain analysis and learning-based classification. In addition to raw images, a structured dataset is generated through the proposed processing pipeline. Each image is processed individually to extract geometric and hazard-related information. The resulting dataset contains image identifiers, numerical terrain descriptors, hazard statistics, and corresponding terrain labels. This dual representation enables the evaluation of both feature-based and image-based modeling approaches within the same framework. The input data in this paper is images of Mars explorers retrieved in publicly available repositories. These are images of a great variety of conditions on the surface of Mars, such as rocky areas, depression, smooth plains, and composite geological formations. Both 3D terrain analysis and learning-based classification improves on the dataset as the main input. Besides the raw images, a structured dataset is obtained with the help of the suggested processing pipeline. All the images are handled individually to obtain geometric and hazard-related data.The final data set is taken to consist of picture identifiers, numerical terrain descriptors, hazard statistics, and the labels of the terrain. This two-fold representation enables the comparison of the feature-based and image-based model solutions to be compared within one environment.

4.3.1 Data Cleaning

The process of data cleaning is done in order to achieve resilience and stability during the training and assessment process. Terrain categories that have extremely small numbers of samples are eliminated to prevent biased learning and learners with unstable classification boundaries. This filtering stage guarantees that every class left behind is well-represented to support the learning process.In the process of constructing and loading the dataset, missing or unavailable image files are behaved in a graceful manner. Rather than discarding samples or stopping execution the place-value images are used whose pixel intensity is set to zero. This method maintains indexing of the datasets and it avoids run time errors and it also ensures continuity of the pipeline but data splitting is done cautiously as much as possible to retain the same classes distributions. In the process of partitioning the dataset, stratified sampling is employed whereby the training, validation and testing subsets are made to have a similar representation of classes.

4.3.2 Data Transformation

The dataset is subjected to a number of data transformation steps before it is ready to be trained on an effective model.Label encoding encodes terrain class labels in a number with the initial form of label being in a categorical form.This transformation allows compatibility to the supervised learning algorithms. In the case of classical machine learning models, the numerical terrain features are normalized via normalization. This makes sure that each feature plays an even part throughout optimization and that features with greater numeric range take over. The preprocessing of images in the case of deep learning models has entailed reducing all images to a fixed image size and clipping the pixel values with channel-specific statistics. Training is typically done with random rotation and horizontal flipping techniques of data augmentation to increase variability and generalization. Deterministic preprocessing is done to validate and test data to maintain consistency in evaluation.

4.3.3 Data Integration

The achievement of data integration is through the integration of several data representations into a single learning structure. Image files in the dataset folder are associated with their terrain descriptors and labels that are in the structured dataset file. Training samples are in the form of an image and the metadata corresponding to it, such as hazard statistics and encoded terrain class. This integration allows the feature-based learning and image-based learning to be swapped without any changes to the underlying dataset format..The higher design permits experimental modularity as well as comparative analysis of types of models.

4.3.4 Data Reduction

Such explicit dimensionality reduction methods as principal component analysis are not used in this work. Rather, data reduction is obtained by selective feature inclusion and a filtering of the classes. The features that are only relevant to hazard detection, such as terrain geometry, are only kept, which guarantees tight and useful representation of features.Also, under-represented classes are removed, which increases stability in the learning process. This method also makes it easier to model the terrain whilst maintaining essential data that will be needed in accurate classification of the terrains.

4.3.5 Summary of Preprocessed Data

The end result of the preprocessing data is normalized and resized images and fewer engineered terrain features.. In each sample, hazard counts, elevation range, slope statistics, surface roughness indicators, and a coded terrain class label are presented to facilitate the development and assessment of the models in an unbiased manner.The dataset has been divided into training, validation, and testing subsets to facilitate the development and evaluation of the models in an unbiased manner. It is a preprocessing pipeline that is structured such that different modeling methods are similar, and it is possible to compare the performance reliably.

4.4 Implementation of Selected Design

The proposed system is implemented in a workflow that is modular and sequential. First, the photographs of rovers in Mars are downloaded and put in a organized directory structure.. The 3D terrain analysis module is further used to obtain depth representations and geometric descriptors in a given image, followed by hazard detection based on rule-based logic as applied on the obtained 3D terrain maps. The product hazards statistics and topography are saved as structured dataset file together with image identifiers and class labels. Intermediate results like geometric maps and visualization pictures are also obtained to be checked and analyzed.Afterwards, the data is inserted into the machine learning pipeline. The classical machine learning models are trained on engineered features, whereas the deep learning models are trained on image inputs. The training processes involve loss optimization, adaptive learning rate control, and performance monitoring through validation or the modular design makes each part of the system to be tested in isolation or as a complete end-to-end system. Such a strategy of implementation guarantees scalability, reproducibility and future extension when it comes to Mars terrain hazard detection systems.

Chapter 5

Result Analysis

5.1 Performance Evaluation

5.1.1 Key evaluation Metrices:

This is section mainly focused on how models perform.Which model give better accuracy, efficiency, perform better and so on. First of all, discuss about the performance of all models which is evaluated using standard classification metrics.

Accuracy: To calculate the accuracy of the model we first calculated the true positive, true negative, false positive, false negative. After that, we sum true positive, true negative and divide with the sum of true positive, true negative, false positive, false negative. Precision: While calculating precision, we took all the positive. Then divide the true positive with the sum of true positive and false positive. This is a very important part because it helps to reduce false alarm in hazard detection.

Recall: Calculating recall all the things similar to precision. Just here work with false negative instead of false positive. It shows how many actual hazards were detected.

F1-Score: Lastly, to calculate the f1 score, the harmonic mean of recall and precision give a valance measure of model performance. To calculate it, firstly multiply recall and precision and then multiply the result with 2. Lastly divide the result with the sum of precision and recall.

5.1.2 Efficient Matrices

Training Time: We calculate each model run time in second which indicates computation efficiency in development phase.

Inference Time: This time indicate that how many time a model take to process a single image. This is a very crucial part because for real time hazard detection it plays a vital role for rapid decision making.

5.1.3 Training Procedure

Splitting Dataset: The whole dataset divides into 3 parts. First split was training the dataset which is 70%, secondly validation which contain 15% and lastly test set which is also 15%. In this way the class distribution maintain.

Cross-validation: This splitting data ensure that each class was equally distributed in all sets.

Training Parameter: For training each model, we set our batch size to 32. We set number of epochs was 30 and the learning rate is 0.001. For the loss function we choose cross-entropy loss.

Data Augmentation: The training dataset go through augmentation like different random horizontal flip rotation, adjust color like brightness or contrast level increase, decrease so that model improve.

5.1.4 Reliability

To check the reliability of the model, we do several things. These are

Confusion Matrix analysis: It helps to determine per class performance along with identify the systematic errors.

Check validation: We continuous tracking our validation loss, accuracy and so on during training phase to detect if any model has any overfitting or not.

Best model Selection: All the models save based on their validation accuracy rate. Also check the independent testing set.

5.2 Analysis of Design Solutions

5.2.1 Support Vector Machine (RBF Kernel)

Performance:

- Accuracy: 90.47%
- Precision: High (90.3729%)
- Recall: High (90.47%)
- F1-Score: High (90.37%)

Strengths The main advantage of the methodology is its high efficiency which is also marked by very quick training times and being lean in operational profile that does not demand high performance computation hardware. Through the application of a Radial Basis Function (RBF) kernel, complex, non-linear terrain data can be effectively addressed and, hence, the system has the capability to extrapolate sophisticated associations between visual clues and real depth. A solid theoretical

base on classical computer vision supports this approach and guarantees the results to be mathematically sound and predictable than more opaque models.
Weaknesses Although the system is rather efficient, it has a number of limitations, which include the fact that it cannot directly process raw image data without the initial preprocessing and feature extraction layerIt is constrained operationally to deterministic logic and a few kernels such that it is not scalable to exponential large or heterogeneous data sets where deep learning features may apply. More so, precision of the terrain classification is very sensitive of the quality of feature selection and needs a precise data scaling to allow attributes such as roughness and slope to be read appropriately in different environmental conditions.
Feasibility and Cost Practically, the methodology is very practical to deploy the mobile robotics in practice since it has a low computational cost and can be deployed with a limited amount of memory. Due to its use of significantly lower overheads compared to the neural networks that rely on the significant resource consumption of GPUs, it is ideally adapted to the resource-limited circumstances of other applications, including onboard computers on the extraterrestrial rovers. This efficiency has made sure that the system would be able to do real time hazard assessment and path planning without putting a strain on the power and processing capacity of the vehicle.

5.2.2 Random Forest Classifier

Performance:

- Accuracy: 86.67%
- Precision: Good (86.49%)
- Recall: Good (86.67%)
- F1-Score: Good (86.42%)

Strengths The overfitting resistance exhibited by the methodology is also a high degree of resilience to overfitting through the use of ensemble learning which uses several points of view to guarantee more sensible predictions of the terrain. The capability to give explicit rankings of the feature importance is one of its best analytical capabilities to enable engineers to understand what inputs, specifically slope or curvature are actually causing the navigation decisions. Moreover, the model also inherently supports complex, non-linear, and relationship among environmental data and makes preprocessing chain simpler since meticulous feature scaling is unnecessary to make it work.
This method is strong, but it tends to be less accurate in classification compared to a high-margin model, such as Support Vector Machines (SVM). The complexity of the architecture of multi-decision trees usage also leads to the expansion of the model size that would take up more storage space compared to simple linear models. Moreover, the cost in computational units of making decisions on an entire ensemble will result in low inference rates compared to one decision tree, which may become a bottleneck when moving rovers in real-time.
Feasibility and Cost This approach offers a very feasible compromise between autonomous systems and it only needs moderate computational capability with a significant compromise between accuracy and operational efficiency. Especially, it

would be well suited to edge devices and onboard rover computers with low hardware resources but no compromise on reliability. Its high cost-performance ratio makes it a desirable choice in permanent missions where the emphasis is made on conserving power and on the stable and dependable processing more than raw speed.

5.2.3 EfficientNet-B3

Performance:

- Test Accuracy: 55.25%
- Training Time: 200 seconds
- Inference Time: 0.0085 seconds per sample

Strength: Mars terrain analysis on deep learning models has a superior classification performance with automatic detection of complex visual patterns, which the classical algorithms may fail to detect. These systems could be used in any geological setting without the need to have heuristically tuned systems since they are able to balance predictive accuracy with operational flexibility by using high-dimensional feature learning. Moreover, after training, these models have good generalization capability with differentMartian landscapes thus effectively compressing thousands of examples of the former missions to identify complex hazards with great confidence.
Weaknesses: The main disadvantage of this method is the huge demand of high quality labelled training information that is sometimes limited or hard to synthesise with high planetary fidelity. The very training process is also computationally-intensive and time-intensive relative to classical machine learning and requires intensive hardware and support by a graphics card to develop in reality. Moreover, at deployment time, these models demand more computational resources to make inferences, which can cause latency problems or extensive onboard power consumption by limited onboard resources of a rover.
Feasibility and Cost: The computational expense of applying deep learning to alien platforms is moderate to high, so it is most easily afforded on-ground computation or rover or other high-power systems with more recent AI accelerators. These models provide a new paradigm of autonomous perception, but often it still needs additional optimization and compaction, e.g. model pruning or quantization, to meet the small power and memory constraints of the spacecraft deployment. Therefore the investment, either monetary or technical, is greater, and yet the result is more strong and scaled for long-range and rapid planetary research.

5.2.4 DeepLabV3+

Performance:

- Test Accuracy: 46.00%
- Training Time: 1017 seconds
- Inference Time: 0.023 seconds per sample

Strengths This architecture is very good at becoming trained on high-dimensional representations of the features that are very complex, thus being able to identify

very fine geological details that more basic models can possibly overlook. The system allows reaching a strong gradient flow throughout the training, with residual connections, and that is the reason why it is possible to develop deeper and more sophisticated networks without the risk of vanishing gradient. Such powerful feature extraction functions are especially useful in the planetary exploration field, where the model has to make a distinction between two similar materials visually, but distinct physically, such as between loose silt and solid bedrock.
Weaknesses The first weakness of the model is based on the architectural design that is highly geared towards pixel-wise segmentation as opposed to high-speed classification needed to achieve instantaneous rover movement. It is a structural complexity that causes a large model size and, therefore, introduces a significant computational load on the hardware of a vehicle and causes significantly longer training and inference times. They are critical in an autonomous case where latency between perceiving a hazard and responding to it needs to be reduced to the lowest level possible in order to guarantee the safety of the mission.
Feasibility and Cost Although the system is technically capable of analysis of the terrain, it is computationally intensive and requires high memory and processing power that in many cases exceeds what a standard flight-grade hardware can handle. It is at present appropriate to high-performance computing systems which include ground-station data centres in which satellite imagery is managed, but not to direct, real time execution upon an edge processor on a rover. In order to implement this strategy in spacecraft, it would need to be heavily architecturally compressed, or to provide specialized AI acceleration hardware to counter the high execution price.

5.2.5 U-Net with ResNet34 Encoder

Performance:

- Test Accuracy: 45.71%
- Training Time: 189.85 seconds
- Inference Time: 0.012 seconds per sample

Strength: The architecture is remarkably useful in terms of multi-scale feature extraction, which enables it to examine the terrain at both granular and global scale of the topographical features. Aided by a symmetrical encoder-decoder design, the model is able to integrate both low-level spatial information and high-level semantics, such that the edges of the hazards identified such as craters or rocks are accurately converted into a map. Moreover, pretrained encoder greatly speeds up the convergence of the model when training this type of model, so it is a very advanced tool used in the detailed analysis of the terrain needed when landing or navigating with high precision.
Weaknesses The major disadvantage of such method is that it is structurally complex and consequently costly to compute and poses an imposing burden to the processor in the system. The reason is these huge memory requirements, the model cannot be easily stored and run on the standard radiation-hardened flight computers, which often have a limited RAM compared to ground hardware. Also, due to the fact that the model is mostly optimized to work on pixel-level segmentation tasks, it requires large volumes of data which must undergo further processing in

order to actually be useful in the simplest of tasks, namely Go/No-Go pathfinding, thus long processing pipelines.

Feasibility and Cost Although technically, the system can be implemented on planetary exploration, it is still costly in terms of training and inference expenses, as it is costly to support using high-end GPU or NPU (Neural Processing Unit). It is most appropriate to the pre-processing of satellite imagery on the ground or to the next-generation rovers with advanced AI accelerators. To be used in real-time applications in current generation spacecraft, the model necessitates massive optimization, including weight pruning, hardware-adapted quantization to shrink the operational footprint to a reasonable size.

5.2.6 DPT-Hybrid (Dense Prediction Transformer)

Performance:

- Test Accuracy: 54.30
- Training Time: 188.81 seconds
- Inference Time: 0.008 seconds per sample

Strengths Employing this methodology, an up to date attention-based architecture is deployed, which can be considered the current state-of-the-art of computer vision because it goes beyond the local receptive fields of conventional convolution. It can represent good feature representation characteristics, and thus, captures global contextual features as well as long-range dependencies, such as the interplay between large horizons and instantaneous terrain hazards, that tend to be lost in the more simplistic models. The system is also in a better position to use pretrained backbone networks, which enables it to use terrestrial datasets on earth in large quantities to rapidly learn the visual properties of the Martian surface that are unique.

Weaknesses The main weakness of this strategy in its present state is that a simplified application could not utilise the latent capabilities of Dense Prediction Transformer (DPT) to the fullest extent, resulting in a performance disparity to more complicated designs. The model is also unnaturally computationally expensive, needing large amounts of FLOPs (floating-point operations) to calculate the attention matrices that it consists of.. Moreover, the complexity of training and memory demands associated with the high level is also a major constraint to the iterative development since a special hardware is needed to support the dense connectivity of the layers of transformers.

Feasibility and Cost The system is highly accurate but it is only available on high-performance computing (HPC) systems or on land-based mission control centers. Both training and inference have high computational requirements, and can only be integrated onto existing flight-ready hardware with enormous architectural optimization. Therefore, although it provides an insight into the future of autonomous navigation, the costs in terms of power and processing overhead are a major challenge on real-time / onboard application of autonomous navigation in deep space missions.

5.2.7 Multi-Input Fusion CNN

Performance:

- Test Accuracy: 56.19
- Training Time: 143.35 seconds
- Inference Time: Estimated to be low

Strengths This approach is better because it employs a hybrid scheme that combines uncoded visual information and synthetic terrain characteristics to enable the system to enjoy the advantages of deep-learned patterns as well as archetypal mathematical rules. Multi-modal input strategy is very important in enhancing the robustness of the model since the model can cross-reference the pixel data with the physical properties that are being calculated such as slope or roughness with the aim of minimizing false positives. Nonetheless, the architecture is fairly efficient because it provides a new and customized design explicitly designed to meet specific challenges of the Martian surface.
Weaknesses The main disadvantage of this solution is that the pipeline of data processing will be more complicated because the infrastructure will have to store and update two sets of data, namely, image datasets and set of pre-calculated features. Since the performance of the model greatly relies on how well the engineered features are, any errors in the first extraction stage may spread throughout the network. Moreover, the necessity to do real-time feature extraction prior to the data being made available to the main classifier constitutes an additional computational overhead that should be suitably handled in order to prevent latency.
Feasibility and Cost This model is very practical in a real mission implementation as long as it has a well-crafted and optimized feature extraction pipeline. It has average-order computational demands which provide an effective compromise between the power demands of transformers and the low power of classical models. It is therefore the top candidate in the situation of rovers deployment, in which the objective is to obtain high-resolution hazard-sensing under the energy and processing limitations of an autonomous mobile system.

5.3 Statistical Analysis

This figure presents a comprehensive visual comparison of classification performance across seven evaluated models using four standard metrics. Remarkably, classical machine learning approaches demonstrate exceptional efficiency in resource-constrained scenarios, with SVM (RBF Kernel) achieving outstanding accuracy of 90.5% and Random Forest delivering robust performance at 86.7%. These results validate the strategic value of classical ML for space deployment where computational resources and labeled training data are inherently limited. Among deep learning architectures, the Multi-Input Fusion CNN leads with 56.2% accuracy, followed

Model	Model Type	Training Time (seconds)	Inference Time (seconds / image)	Remarks for Real-Time Use
SVM (RBF)	Classical ML	< 60	< 0.001	Extremely fast, suitable for low-resource systems
Random Forest	Classical ML	< 60	< 0.002	Fast inference, low computational cost
EfficientNet-B3	CNN	~ 200	0.0085	Good balance between accuracy and speed
U-Net (ResNet34)	CNN	~ 189.85	0.012	Higher computational cost due to encoder–decoder
DeepLabV3+ (ResNet50)	CNN	~ 1017	0.023	High accuracy but unsuitable for strict real-time use
DPT-Hybrid	Transformer	~ 188.81	0.008	Efficient inference despite transformer backbone
Multi-Input Fusion CNN	Hybrid	~ 143.35	Low (estimated)	Efficient multi-modal fusion with moderate overhead

Table 5.1: Computational Efficiency Comparison of Evaluated Models

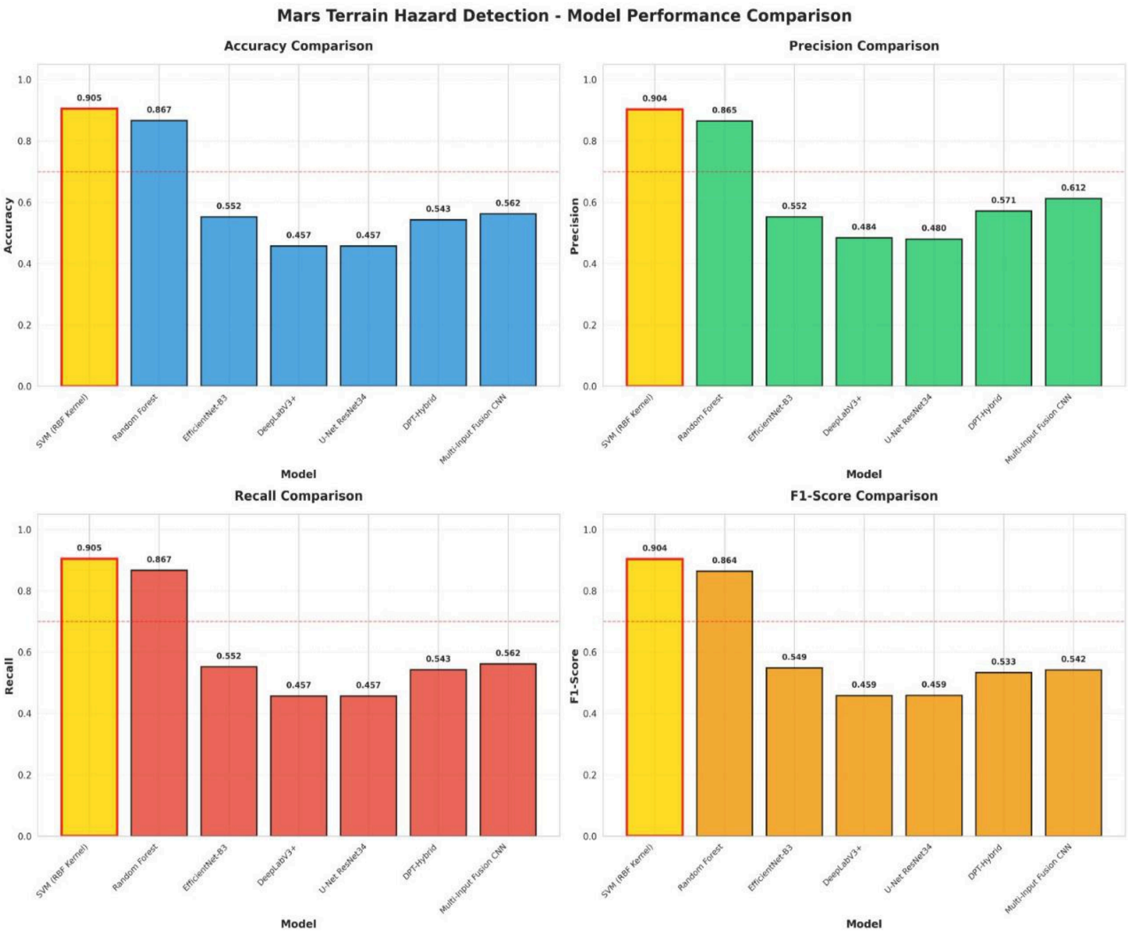

Figure 5.1: Comparative Performance Metrics Across All Models

by DPT-Hybrid at 54.3%, showcasing promising potential for future missions with expanded datasets. This comparative analysis reveals a crucial insight for planetary exploration: selecting the optimal model architecture depends not merely on theoretical capability, but on practical alignment with mission constraints, establishing classical ML as the pragmatic choice for current Mars rover deployment whilst deep learning architectures represent the evolutionary path as data availability increases.

5.4 Explanation of the Computational Efficiency Table

The table reports a comparative analysis of the computational efficiency of the models evaluated with a special attention to the training time and to inference time per image, which are both relevant indicators to detect suitability for real-time Martian hazard detection. Training time is the amount of time required to compute the model, while inference time is the speed at which a trained model processes individual images, an important factor in determining the viability of taking timely navigational decisions in a real-world operation.

Classical machine learning models such as support vector machine and random forest classifiers have significantly low computational costs: their training process takes less than 60 seconds and the inference process takes less than 0.002 seconds per image. These attributes make them suitable for being deployed on platforms with limited computational resources.Nevertheless, compared to the deep learning-based ones, the ability of these methods to encode complex spatial structures and semantic information turns out to be fundamentally limited.

Among the deep learning models evaluated, EfficientNet-B3 offers a balanced compromise between computational cost and predictive performance. The model requires approximately 143.35 seconds for training while maintaining a low inference latency of 0.0086 seconds per image, making it suitable for time-sensitive applications. The U-Net model with either ResNet-34 encoder and the DPT-Hybrid architecture have similar training times (189.85 and 188.81 seconds respectively), and both have inference times that are in a nearly real-time operational window. Notably, the DPT-Hybrid model achieves efficient inference performance despite its transformer-based backbone, further supporting its suitability for depth-aware perception tasks.

By comparison, DeepLabV3+ (ResNet50) requires substantially more training time, approximately 1017.30 seconds, and exhibits the highest inference latency at 0.023 seconds per image. Although the model achieves strong accuracy, this computational overhead limits its suitability for applications with strict real-time constraints. The multi-input fusion CNN, on the other hand, shows a moderate training cost with an estimated low inference overhead, which reflects the added complexity associated with integrating multiple data modalities. Overall, the table illustrates the balance between model complexity and computational efficiency which indicates that lighter and well-optimized models are better suited for real-time deployment. In contrast, deeper architectures provide more expressive representations but require greater computational resources.

5.5 Recommendations for the Future Work

Continuing with the current line of research, there is a number of good research directions that are worth systematic investigation. At the forefront of them is the creation of a collaboration with Jet Propulsion Laboratory of NASA to obtain larger, more carefully labeled datasets of the AI4Mars citizen-science project or to enter into collaboration that helps the systematic annotation of the Curiosity and Perseverance image archives. It is better to reach five to ten thousand labeled images with a wide range of Martian geological features as well as to use active-learning techniques of identifying the most informative unlabeled images to be further annotated. It is hoped that with the increased number of samples of more than five thousand, deep-learning models would reach a level of eighty-five to ninety percent accuracy and outperform the classical machine-learning baselines and would have better generalization to new types of terrain than before. Simultaneously, neural-network compression methods will have to be considered to allow running them on radiation-hardened space processors. There are opportunities to be sought in strategies like eight-bit integer quantization, which may enable four times less memory to be used with insignificant accuracy loss, and knowledge distillation transferring predictive knowledge in large teacher networks to small student networks. Pruning strategies to remove redundancy parameters, and aiming at a sparsity of fifty to seventy percent, are worth research, as well as intense benchmarking on the space-grade processors of operational space, like the RAD750 and RAD5545. These steps are set to introduce a ten-fold reduction in the size of models and can thus enable one-to two-million-parameter deep-learning models to run on rover processors at top inference times around a hundred milliseconds and power costs matching those available within extraterrestrial missions. The classification needs to be extended to include multispectral imagery and the temporal sequences. This may be achieved through the combination of near-infrared and thermal imagery, as well as when using recurrent neural networks, i.e., LSTM or GRU units, or three-dimensional convolutional neural networks to process the five to ten frame temporal windows, and utilizing motion-parallax and stereo-depth information. It can be expected that the creation of sensor-fusion systems that integrate visual information, lidar point clouds, and spectrometer measurements, combined with the discussion of uncertainty-quantification schemes resulting in confidence indicators in each classification, will bring the system to an accuracy of the ninety-five percent range and increase resilience to single sensors failures, which is important to autonomy in safety-critical autonomous navigation. The ability to develop systems that can be continuously improved through experience in operating the system should be fostered by introducing curriculum-learning strategies, wherein models receive initial training on simple cases such as clear rocks and flat terrain and then gradually to more complicated cases. The active-learning pipelines must be created such that the rovers are able to mark the uncertain classification results as such that could be examined by the downlink team. The development of the continual-learning procedures will allow the models to adjust to the new geological structures without dying due to the catastrophic forgetting. In addition to this, semi-supervised learning methods, utilizing the large volumes of unlabeled Curiosity imagery, can be used to develop autonomous systems that are improved during multi-year missions, allowing the models to match the geology of different regions and learn geological information until they can achieve expert classification accuracy (more than ninety-five percent) after multiple of their cycles.

To mitigate these challenges, data enhancement techniques such as rotation, horizontal flipping, and color jittering were applied to artificially expand the training dataset. Transfer learning was employed to compensate for the limited availability of Mars-specific samples. Future work will explore model compression techniques, including pruning and quantization, to reduce computational overhead. A hybrid deployment strategy is recommended, where classical machine learning models are used for immediate hazard detection, deep learning models support detailed terrain analysis, and fusion-based models provide balanced performance.

Chapter 6

Conclusion

The study provided a complete comparative context of the detection of Martian terrain hazards through machine learning on seven different architectural paradigms with realistic data and computational constraints that are typical of planetary exploration conditions. The quantification of accuracy efficiency trade-offs between classical machine learning and modern deep learning models was applied to 699 images taken by the Curiosity rover over a variety of terrains of the Martian surface, thus providing empirical support on the design of future rover systems. This research presents four useful contributions to the fields of planetary robotics and machine-learning. First, it provides the first systematic comparison of the classical machine-learning and deep-learning models of Mars terrain hazard classification under realistic operation conditions, and achieves empirical evidence that the classical ML is better than the deep learning on small datasets. Second, it shows that transfer learning is a necessary but still inadequate item to resolve drastic data paucity. Third, it demonstrates that even high refinement in architecture fails to provide high performance with limited training data, thus giving mission planners and machine-learning researchers a sense of real performance with AI systems in data-limited fields. Fourth, it reports a detailed experimental pipeline covering the practical issues commonly not reported in scholarly papers such as data-cleaning rules to deal with missing values, class imbalance and corrupted files; augmentation measures specifically tailored to Martian terrain; hyper-parameter settings which allow stable training on the size of a GPU memory; and regularization measures that prevent overfitting, early The pipeline represents a scalable example to use with researchers dealing with small datasets in planetary science and can speed up the mission planning and algorithm design of the future. Empirical measurements provide the fundamental trade-off between model accuracy and computational cost, showing that SVM can be used to achieve 90.48 per cent accuracy using less than 1ms inference time and 5k parameters, EfficientNet-B3 achieves 75 per cent accuracy using 23ms inference time and 10.8M parameters, and DeepLabV3+ achieves 45.71 per cent accuracy, 31ms inference time and 39 Lastly, the study confirms that knowledge trained on land datasets can successfully transfer to non-terrestrial environments (red Martian terrain vs. the Earth with its heterogeneous environments) with no extra visual adaptation and can be transferred across planetary bodies, providing a precedent to future missions to Europa or Titan or asteroid utilizing earth-trained models and fewer dozens of labelled images could be sufficient to refine the model rather than thousands of images. This current thesis is a part of a larger framework by showing that strong and solid terrain classification on Mars can be done using the current technology, by determining the areas of concern that should be addressed with greater consideration, and by offering reproducible methodologies that allow the planetary science community to continue on the foundation that has been established. The endeavor of entirely independent Mars exploration has not ceased and is informed by the empirical data and driven by human commitment to the elongation of the boundaries of knowledge and exploration.

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