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Enhancing Planetary Surface Analysis using a Hybrid Deep Learning Framework: Combining CNN-Based Image Classification with LLM-Driven Semantic Explanations

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ABSTRACT

Accurate identification and interpretation of planetary surface features are critical for advancing extraterrestrial geological research. In this study, we propose a two-stage intelligent framework that combines a Convolutional Neural Network (CNN) with a Large Language Model (LLM) to classify and explain features on the Martian surface. CNN is trained on annotated satellite imagery from NASA's HiRISE dataset to detect surface structures such as craters, dunes, slope streaks, and impact ejecta. Once a class is predicted, the output is passed to a state-of-the-art LLM (Meta's LLaMA-4 model accessed via Groq API), which generates human-readable scientific explanations for the detected features. Our system not only identifies features accurately but also explains them clearly. This shows how AI can help scientists better understand planets and could be useful for future space missions.

KEYWORDS: *AI for Space Research*

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1. INTRODUCTION

While Large Language Models (LLMs) offer powerful capabilities in generating human-readable explanations, they typically require massive amounts of data to perform well, especially for visual understanding tasks.

The main goal of this project is to address this challenge by introducing a two-stage pipeline that avoids feeding raw images directly into an LLM. Instead, we first use a Convolutional Neural Network (CNN) for classifying Martian surface features. CNNs are more suitable for computer vision tasks when data is limited, and they have shown to perform accurately even with relatively small datasets. In our project, CNN is trained to detect and classify key Martian features like craters, dunes, and other surface structures. These classifications are then passed as input to a state-of-the-art LLM—specifically, Meta's LLaMA-4 model, accessed through the Groq API. This approach is particularly beneficial in our case, as the Mars dataset we work with suffers from a lack of large-scale labeled data.

By using a CNN to handle feature classification and then passing the output to an LLM for explanation generation, we combine the strengths of both models.

2. Related Work

Machine learning techniques, particularly Convolutional Neural Networks (CNNs), have been effectively employed in planetary science for the classification of surface features. For instance, Shozaki et al. (2022) developed neural network models to classify Martian chaos terrains, utilizing imagery machine learning to analyze over 1,400 surface images, achieving significant accuracy in identifying geological formations linked to groundwater circulation and magmatism on Mars. Similarly, McDonnell et al. (2022) designed deep CNNs trained on data from the Planet Four citizen science project to identify seasonal features in the Martian south polar region, demonstrating the efficacy of CNNs in detecting subtle surface changes. [1]

In the realm of geoscience, Large Language Models (LLMs) have shown promise in contextual understanding and explanation generation. Hadid et al. (2024) [2,3] explored the potential applications of generative AI and LLMs in geoscience, discussing their utility in data generation, simulation, and multi-criteria decision-making challenges related to Earth system dynamics. Furthermore, the INDUS project [4] introduced a suite of LLMs tailored for scientific applications, trained on domain-specific corpora encompassing planetary science, demonstrating improved performance over general-purpose models in specialized tasks.

Despite these advancements, the integration of CNNs and LLMs for scientific interpretability in planetary science remains underexplored. Our work builds upon these foundational methods in computer vision and natural language processing, introducing a novel pipeline that incorporates explainability into automated feature classification, aiming to bridge the gap between complex scientific data and accessible understanding.

3. Dataset

We utilize the annotated dataset from NASA's HiRISE mission, which includes satellite images labeled with surface features such as:

1. Crater

A **crater** is a circular depression on the surface of Mars, typically caused by the impact of a meteoroid or asteroid. Craters often have raised rims and can vary in size from small pits to massive basins.

2. Dark Dune

Dark dunes are sand formations made of basaltic material, which gives them their darker appearance. They are commonly found in Martian craters and are shaped by wind activity, showing patterns like ripples or crescent-shaped barchans.

3. Slope Streak

Slope streaks are narrow, dark marks that appear on steep slopes. They may form suddenly and fade over time. Their origin is still debated but may involve dry avalanches of dust or even small amounts of briny water.

4. Bright Dune

Bright dunes are lighter-colored sand formations, indicating different mineral compositions or surface coatings compared to dark dunes. Their shape and distribution also provide clues about prevailing wind directions.

5. Impact Ejecta

Impact ejecta refers to the material that is thrown out during a meteoroid impact. It usually surrounds craters and can include rock, soil, and dust, forming patterns like rays or lobes.

6. Swiss Cheese Terrain

Swiss cheese terrain is found near Mars's south pole. It features smooth, flat surfaces with round or irregular pits caused by seasonal sublimation of carbon dioxide ice. The patterns resemble Swiss cheese, hence the name.

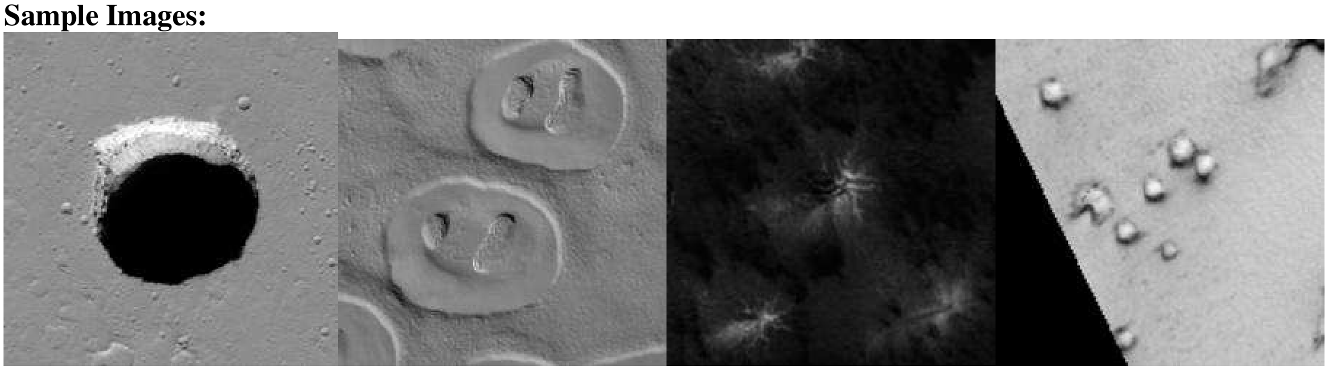
7. Spider Terrain

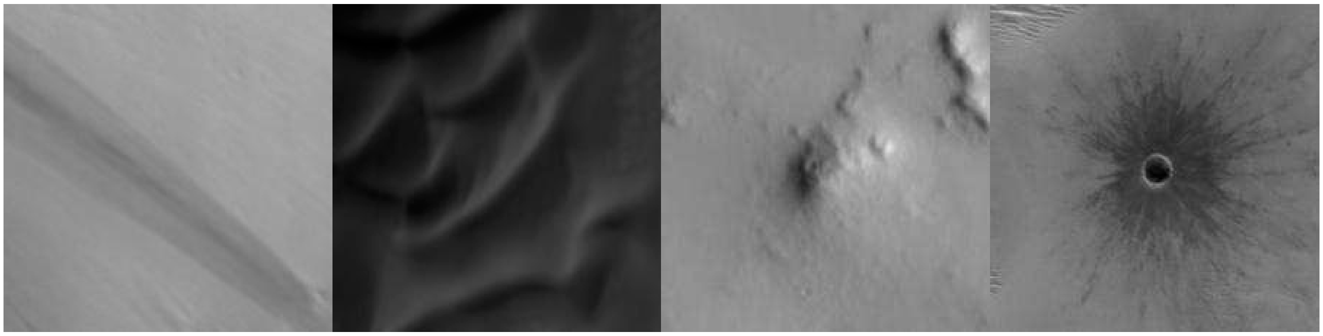
Spider terrain, also called "araneiform terrain," consists of radial channels formed beneath the ice at the Martian poles. They form when gas erupts through CO_2 ice in the spring, carving spider-like patterns in the ground.

8. Other

The **Other** category includes Martian surface features that don't fit clearly into any of the above classes. This can include ridges, plains, layered terrain, or features that are not easily categorized.

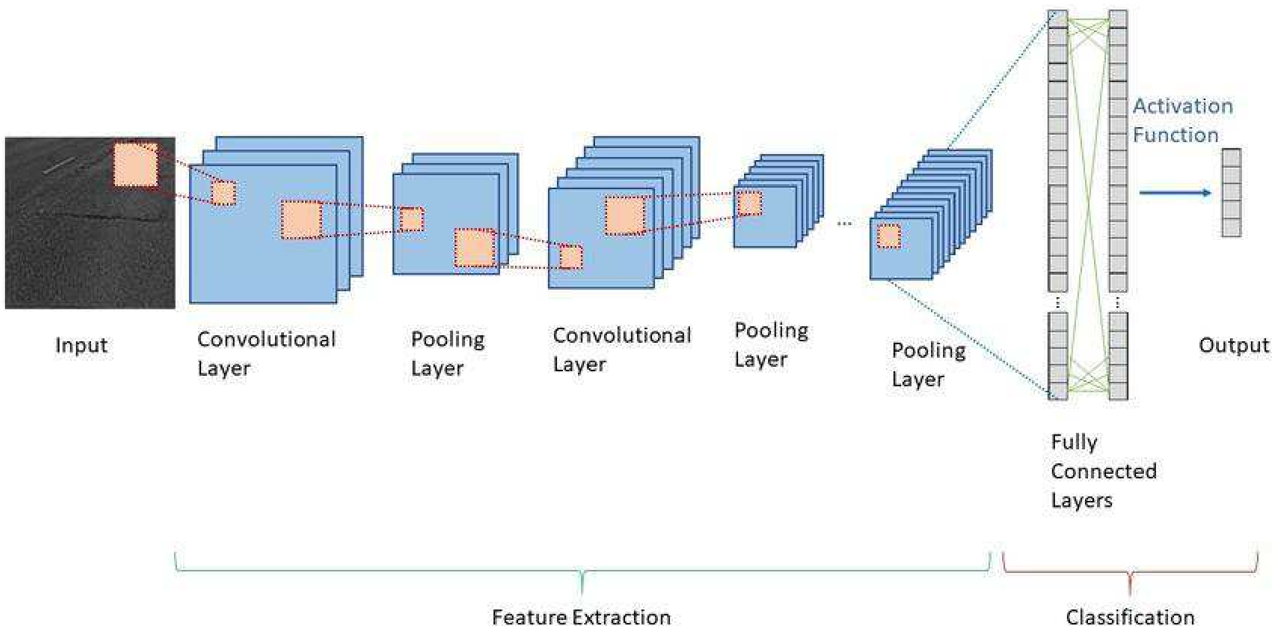
Sample Images:





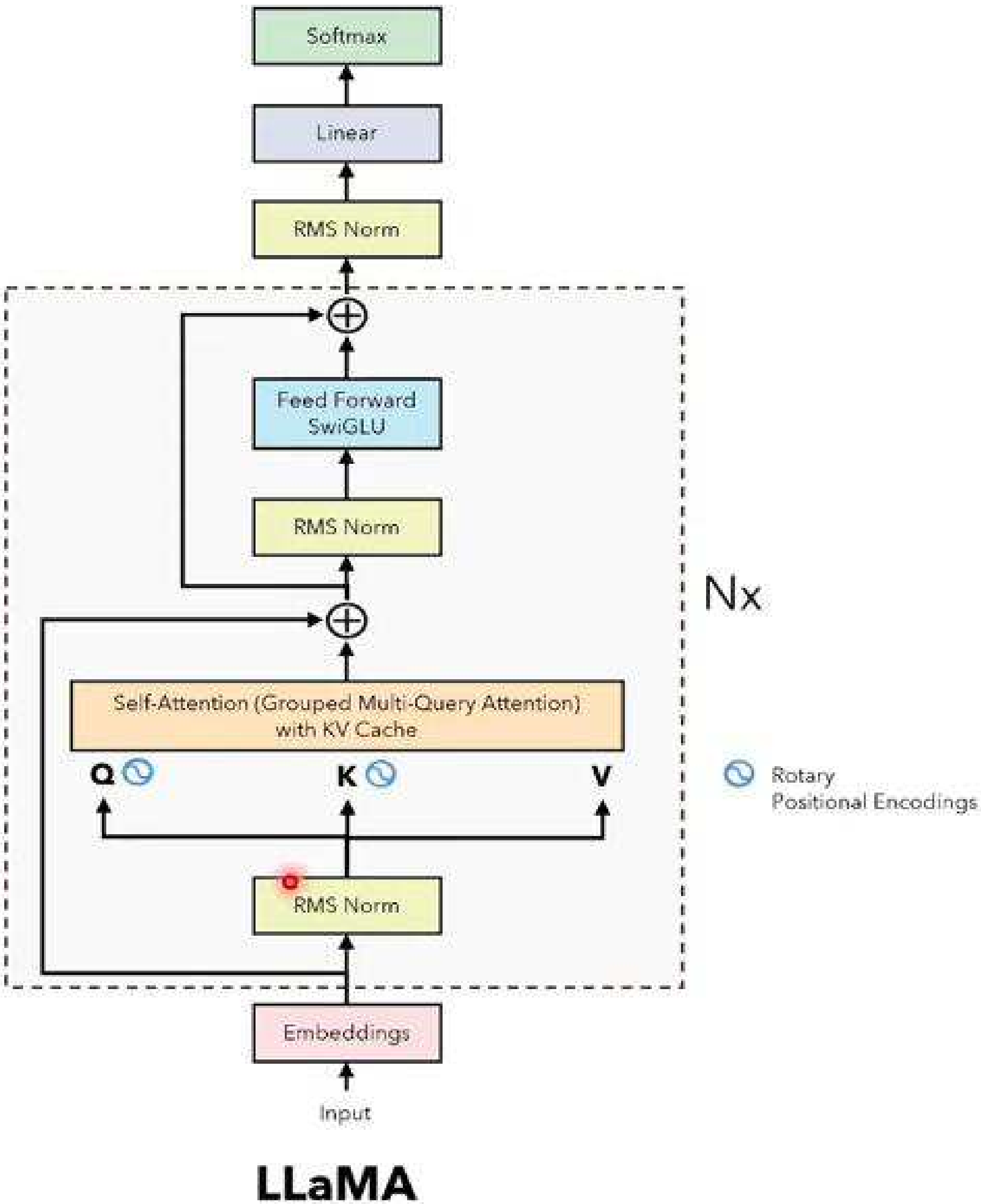
4. Methodology

4.1. CNN-Based Classification A simple yet effective CNN model is designed with three convolutional layers followed by max pooling and fully connected layers. The architecture includes dropout for regularization and ReLU activations. The model is trained using cross-entropy loss and optimized with the Adam optimizer.



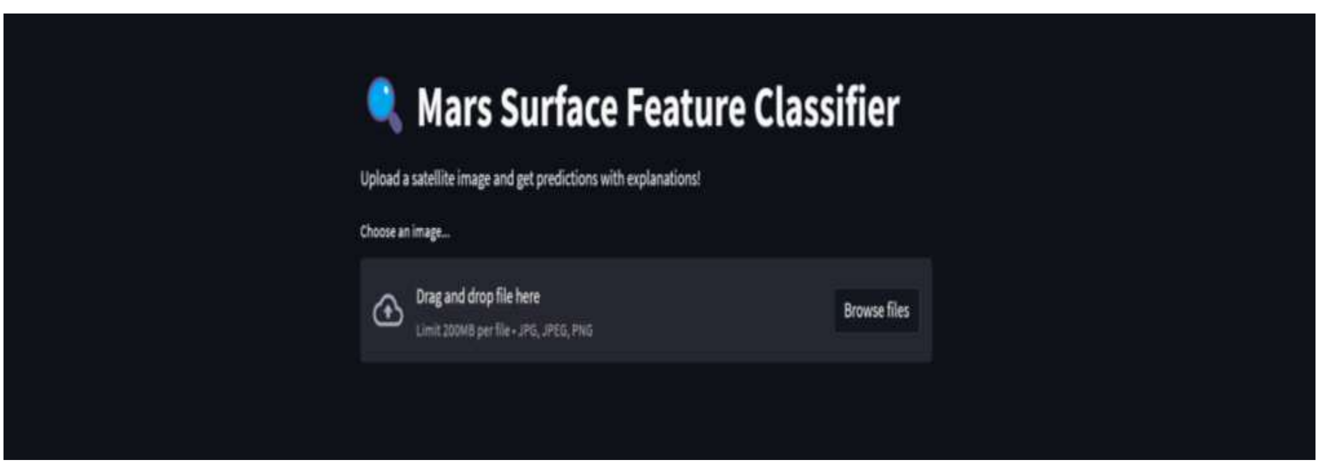
CNN Architecture

4.2. LLM-Based Explanation Generation Following classification, the predicted class label is passed to a Groq-powered API endpoint that uses the Meta LLaMA-4 model. A custom prompt requests a general-audience explanation of the geological feature. The LLM returns a concise, scientifically accurate, and readable summary.

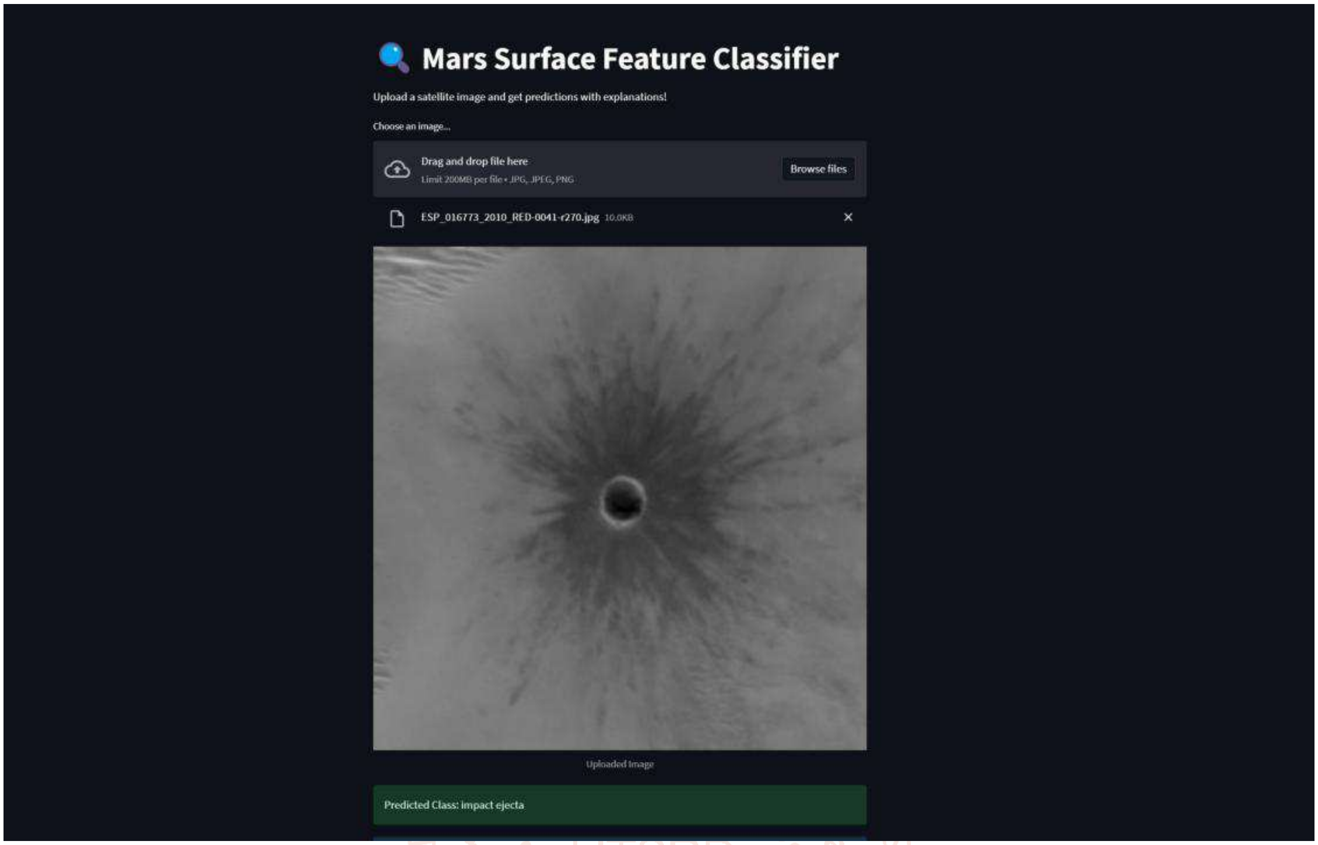


5. Results

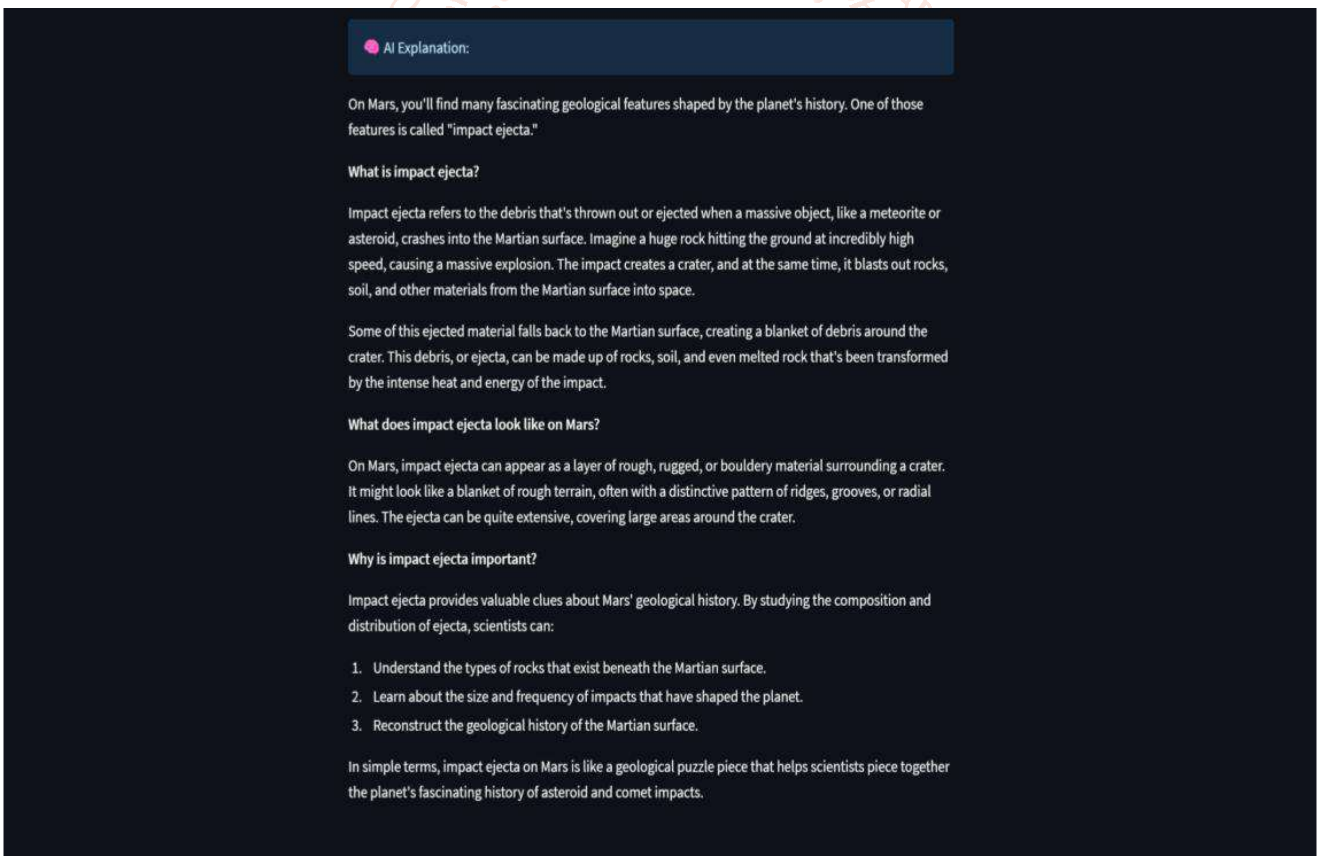
The CNN achieved an accuracy of 87% on the validation set. The explanations generated by the LLM were evaluated qualitatively and found to be clear and scientifically appropriate for related Mars dataset.



Application to upload images



Prediction using CNN model



Detailed expanation using LLM model

6. Conclusion

We created a smart AI system that can both identify and explain different surface features on Mars. It uses deep learning to analyze satellite images and a language model to provide simple, easy-to-understand explanations. This helps scientists study Martian landscapes more efficiently and also makes science more accessible to the public. In our project, we achieved very good results, showing that this combined approach can be both accurate and informative, even when working with limited data.

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