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Identification of Frost in Martian Hirise Images

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Abstract
Understanding Martian landscapes is crucial for unraveling the mysteries of Mars' seasonal frost cycle and its implications on the planet's climate over the last 2 billion years. Discriminating images depicting frost or background in Martian territory are crucial to identifying low latitude frosted microclimates, offering valuable insights into climate patterns and surface evolution. Accurate classification of these images is paramount in understanding Martian climate dynamics. This work proposes a comprehensive system to build classifiers that distinguish images of Martian terrain from frost. The dataset, sourced from the Jet Propulsion Laboratory (JPL Open Repository), California Institute of Technology, NASA, provides a rich repository of Martian images, forming the foundation for our classification endeavors. Neural networks are adept at capturing complex patterns and subtle features within image data, making them well-suited for discerning the nuances associated with Martian terrain. The proposed CNN+MLP architecture employs convolutional layers for feature extraction, capturing spatial hierarchies in the images, followed by MLP layers for further abstraction and classification.

Keywords: *Martian landscapes, Seasonal frost cycle, Martian climate, Low latitude, frosted microclimates, Climate patterns, Surface evolution, Image classification, Martian terrain, Frost detection, Jet Propulsion Laboratory (JPL), California Institute of Technology, NASA, Neural networks, Convolutional Neural Networks (CNN), Multi-Layer Perceptron (MLP), Feature extraction, Spatial hierarchies, Image data, Classification system, Mars exploration.*

1. Introduction

Mars, with its extreme climate and geological diversity, presents a significant challenge in understanding its climatic history, particularly in relation to its seasonal frost cycles. The ability to accurately classify Martian surface images for the presence of frost is critical for interpreting the planet's climatic conditions and geological evolution over billions of years. However, the current classification systems are hindered by limited datasets and generalized feature extraction methods that inadequately capture the subtleties of Martian frost. Consequently, there is a pressing need for a sophisticated classification system capable of effectively discerning frosted terrains from the diverse Martian landscape. This project addresses this gap by proposing a novel machine Learning framework, utilizing advanced neural network architectures and transfer learning techniques. The goal is to significantly enhance the accuracy of frost classification in Martian images, thereby enabling a more nuanced analysis of Mars' climate dynamics and assisting in the broader objectives of planetary science and exploration. This study embarked on the ambitious task of classifying Martian HiRISE images into categories indicating the presence or absence of frost, utilizing a combination of Convolutional Neural Networks (CNN) with Multilayer Perceptrons (MLP) and the integration of advanced transfer learning models includingEfficientNetB0, ResNet50, and VGG16.

2. Literature Survey

Liu, Y., et al proposed "Automated Detection of Geological Features on Mars Using Convolutional Neural Networks" in the Year 2018. The study uses Convolutional Neural Networks (CNNs) to detect Mars geological features, including craters and dunes, using high-resolution images from the HiRISE camera, demonstrating their high accuracy in

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planetary science.[1] Tao, X., et al proposed "Deep Learning for Automated Detection of Mars Surface Changes Using HiRISE Images" in the Year 2019. This paper presents a deep learning method for detecting Martian surface changes using temporal HiRISE images, enabling high precision identification of landscape changes like new craters or shifting dunes.[2] Smith, A., et al proposed "Remote Sensing of Frost on Mars Using Thermal Imaging and Machine Learning" in the Year 2017. The study uses thermal imaging data and machine learning algorithms to detect frost on the Martian surface, enhancing detection accuracy and robustness through deep learning. [3] Rem Martinez, J., et al proposed "Identification of Seasonal Frost on Mars Using Deep Learning Techniques" in the Year 2020.This study uses deep learning to identify seasonal frost patterns on Mars, enhancing accuracy over traditional image processing methods, providing a practical reference for methodologies and expected outcomes.[4] Gupta, R., et al proposed "Enhancing Mars Surface Feature Detection with Data Augmentation and Transfer Learning" in the Year 2021. This paper discusses the use of data augmentation and transfer learning to enhance the detection of surface features on Mars. Highlights the effectiveness of deep learning in analyzing Martian surface features and detecting environmental changes, particularly in detecting frost in HiRISE images.[5]

3. Overview of the Project

A dataset of ~30,000 labeled HiRISE image tiles has been curated to study the Martian seasonal frost cycle and its impact on the planet's climate and surface evolution. The study aims to quantify frost coverage in the Martian northern hemisphere using HiRISE observations and identify trends in frost formation and stability. A qualitative scale is assigned to images based on frost coverage, and a method is developed to quantify frost using QGIS software. Researchers have developed a Dust Image Classifier with 94.05% accuracy to automatically filter out HiRISE images obstructed by atmospheric dust. An Auto Encoder-based denoiser and Pix2Pix GAN are used to denoise partially obstructed images, achieving SSIM Index values of 0.75 and 0.99 respectively. A CNN classifier called HiRISE- Net has been developed to classify images from the HiRISE dataset, achieving 81% accuracy on testing data. This replicates the "Deep Mars" paper by Wagstaff et al., which focused on classifying Mars imagery using CNNs. The sublimation of Mars' southern seasonal CO_2 cap has been imaged by HiRISE at high resolution, revealing enigmatic features with no earthly analogs.

4. Training Dataset

This study aims to distinguish between images with small ice patches and those without. HiRISE images were collected and organized into two groups, which the program learned to distinguish between. The images were chunked using the Mars Orbital Data Explorer Access software, which removed chunks with black pixels around the center of the image. The uniform chunk size is 1024 pixel by 1024 pixel, which is necessary for surface features to be considered during the training process. The images were converted to grayscale before chunking to improve training time. Out of 110 HiRISE images, 34 were selected for training, with 26 having small icy patches and 9 with none or visible CO_2 sublimation on the surface. The dataset was expanded to 6492 images, sufficient for training a CNN. Chunks from the 26 icy images were individually categorised into icy and not icy chunks to ensure data organization. A bright patch is considered icy if it is located on the poleward side of a shadowing landform, does not cast shadow, and has slightly diffuse edges. 252 chunks with difficult- to-identify bright patches were left out of the training process. After chunking and categorising, the dataset of 34 images was expanded to 6240 image chunks. Out of these, 42% showed small ice patches visible, remaining chunk show co2.

5. System Study

5.1. Feasibility Study

The study explores the use of deep learning to automatically identify frost deposits in high resolution images captured by the Mars Reconnaissance Orbiter, a crucial method for understanding Mars' climate cycles and water ice distribution. The feasibility depends on a large dataset and a deep learning model.

5.2. Operational Feasibility

Operational feasibility for the project "Identification of Frost in Martian HiRISE Images Using Deep Learning" involves assessing its practicality and

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usability within the operational context. Design an intuitive user interface for accessing and interacting with the deep learning model, ensuring ease of use for scientists, researchers, and other stakeholders. Provide comprehensive training and documentation to users to ensure they can effectively utilize the model. Provide remote access capabilities to allow users to access the model from different locations. By addressing these operational feasibility aspects, you can enhance the usability and effectiveness of the project, ensuring it meets the needs of its users and operates smoothly within the operational environment.

5.3. Economic Feasibility

Economic feasibility for the project "Identification of Frost in Martian HiRISE Images Using Deep Learning" involves assessing its financial viability and potential economic benefits. By assessing the economic feasibility of the project, you can determine if it is financially viable and if the expected benefits justify the costs. This analysis will help ensure that resources are allocated effectively and that the project

5.4. Technical Feasibility

Technical feasibility for the project "Identification of Frost in Martian HiRISE Images Using Deep Learning" includes considerations related to hardware software, and security. Ensure access to high-performance computing resources, such as GPUs or clusters, to handle the large amount of image data and the computational demands of deep learning. Use libraries like OpenCV for preprocessing HiRISE images and preparing them for input into the deep learning model. By addressing these technical aspects, you can ensure that the project is feasible from a hardware, software, and security standpoint, enabling successful implementation of the deep learning model for frost identification in Martian HiRISE images.

6. System Requirements

6.1. Hardware Requirements

1. Processor
2. Random Access Memory (RAM)
3. Storage

6.2. Software Requirements

1. Operating Platform
2. Integrated Development Environment (IDE)
3. Programming Language

7. Methodology

7.1. Convolutional Neural Network

A Convolutional Neural Network (CNN) is a prevalent type of deep learning model primarily used for processing visual data across various domains. CNNs find applications in image and video recognition, recommendation systems, natural language processing, medical imaging, and financial analysis. Typically, a CNN architecture comprises an input layer, an output layer, and several hidden layers. (Refer Figure 1)

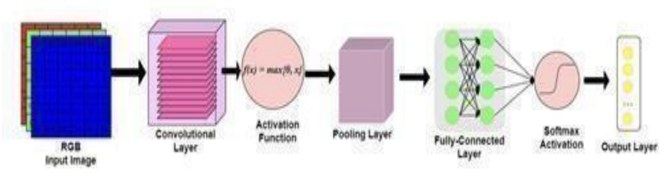

Figure 1 CNN

7.2. CNN with MLP

The combination of Convolutional Neural Networks (CNN) and Multilayer Perceptrons (MLP) presents a powerful architecture for image classification tasks, particularly well-suited for the project goals.

CNNs are highly efficient in extracting hierarchical spatial features from images due to their convolutional layers, which progressively capture low to high-level features.

7.3. Transfer Learning

Transfer learning is a pivotal technique in machine learning that involves repurposing a model developed for a specific task to serve as a foundational starting point fora different but related task.

7.4. VGG16

VGG16 is a Convolutional Neural Network(CNN) architecture that has been widelyrecognized for its effectiveness and simplicity in the field of visual object recognition. Developed by the Visual Geometry Group at the University of Oxford and named for its 16 weighted layers, VGG16 is notable for its uniform use of 3x3 convolutional filters with a stride of one and 2x2 max pooling filters with a stride of two, a configuration it applies consistently. This disciplined approach to architecture design reduces the complexity of hyper-parameter tuning, relying instead on depth to improve performance. With roughly138 million parameters, VGG16 is a heavy

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architecture, yet its popularity persists due to its robustness in various visual recognition tasks. (Refer Figure 2)

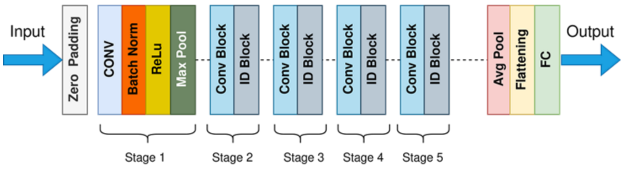


Figure 2 VGG16

7.5. ResNet50

Results Summary ResNet50 is a profound CNN architecture from Microsoft, which has significantly influenced the computer vision domain. The number '50' denotes the 50 deep layers it comprises, each contributing to the network's ability to learn. Its claim to fame is the introduction of 'residual blocks' that help alleviate the vanishing gradient problem by enabling training of very deep networks. ResNet50 is equipped with fewer parameters compared to some of its contemporaries, standing at about 25 million, which allows for a relatively efficient computation. The model is known for using skip connections, or shortcuts to jump over some layers, which helps in the training of deep networks by allowing the gradient to flow through the network directly. (Refer Figure 3)

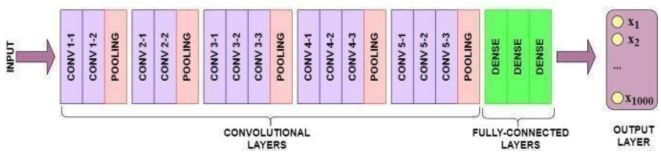


Figure 3 ResNet50

7.6. EfficientNetB0

EfficientNetB0 is a newer entry in the field of CNN architectures, designed with the principle of model scaling. This model standsout due to its compound scaling method, which systematically balances network depth, width, and resolution, leading to better efficiency and performance. As the base model in the EfficientNet family, EfficientNetB0 uses a multi- dimensional scaling approach that carefully calibrates the model's dimensions to maximize accuracy. With fewer parameters than many traditional CNNs, it operates with exceptional efficiency without compromising on effectiveness.

7.7. System Testing

The evaluation metrics utilized to assess the model's performance include Loss, Accuracy, Precision, Recalland F1 Score. This is a measure of how well the model performs, with a lower loss indicating a better model. It is a summation of the errors made for each example in training or validation sets.

7.8. CNN+MLP Evaluation

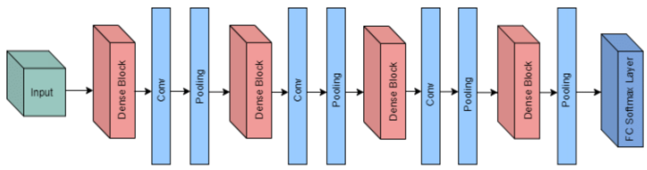
In the evaluation phase of our CNN+MLP model, we employed a comprehensive strategy to rigorously assess its performance on binaryclassification tasks.

7.9. Transfer Learning Models Evaluation

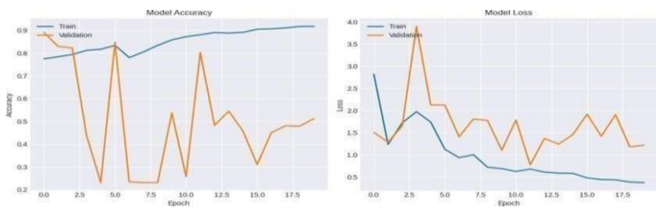
The evaluate_model` function represents a vital component in the assessment of our transfer learning models, providing a quantitative analysis of their performance on the test dataset. Initially, the function undertakes the evaluation of the model to retrieve the loss and accuracy metrics. The loss metric reflects the model's average error across all predictions, offering a perspective on the overall model performance, while accuracy presents a straightforward percentage of predictions the model got correct across the testset. (Refer Figure 4)

```
250/250 [==============================] - 53s 211ms/step - loss: 0.5972 - accuracy: 0.7866
250/250 [==============================] - 44s 174ms/step
Loss: 0.5972364544868469
Accuracy: 0.7866281867027283
Precision: 0.7238775785357962
Recall: 0.929857984066505
F1 Score: 0.8140398756728071
```

(a)



(b)



(c)

Figure 4 (a), (b), (c) Transfer Learning Models Evaluation

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8. Results

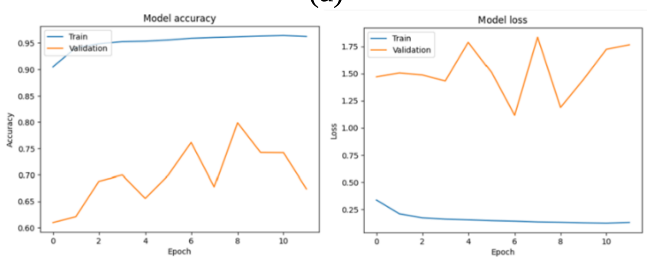
The Results are shown in Figure 5, 6, 7.

```
401/401 [==============================] - 162s 376ms/step - loss: 0.1632 - accuracy: 0.9523
401/401 [==============================] - 157s 352ms/step
Loss: 0.163221225643158
Accuracy: 0.9523143471717834
Precision: 0.5800446668617357
Recall: 0.6155085741714785
F1 Score: 0.6045682145632541
```

Figure 5 EfficientNetB0 Evaluation

```
401/401 [==============================] - 270s 290ms/step - loss: 0.7556 - accuracy: (
401/401 [==============================] - 274s 285ms/step
Loss: 0.155621225643158
Accuracy: 0.9520143471717834
Precision: 0.5904746388617357
Recall: 0.6233088741114423
F1 Score: 0.6064476546377378
```

(a)

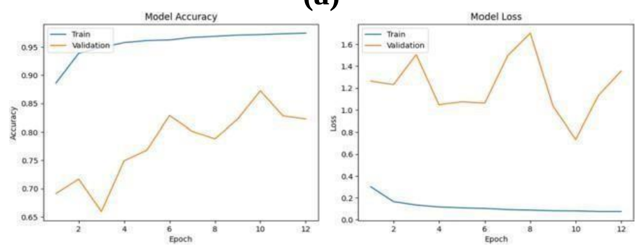


(b)

Figure 6 (a), (b) EvaluationResNet50 Evaluation

```
401/401 [==============================] - 156s 388ms/step - loss: 0.7583 - accuracy: 0.9259
401/401 [==============================] - 145s 362ms/step
Loss: 0.758321225643158
Accuracy: 0.9259143471717834
Precision: 0.6579881656804734
Recall: 0.7276621058893515
F1 Score: 0.6910734463276835
```

(a)



(b)

Figure 7 (a), (b) VGG16 Evalution

Transfer learning models based on EfficientNetB0 and ResNet50 architectures showed outstanding accuracy over 95%, indicating their strong generalization abilities derived from pre-training on diverse datasets. The CNN+MLP model, while having lower accuracy and higher loss, displayed higher precision and recall, suggesting a keenness in identifying true positives but a tendency towards overfitting. The CNN+MLP's higher F1 score reveals its proficiency in maintaining a balance between precision and recall, beneficial in applications where missing positive instances is particularly critical. The transfer learning models' lower precision relative to their high accuracy reflects a cautious prediction strategy, preferring to avoid false negatives, which highlights the trade-offs to consider when selecting a model for specific application requirements.

Conclusion

The study used Convolutional Neural Networks (CNN) with Multilayer Perceptrons (MLP) and advanced transfer learning models to classify Martian HiRISE images based on frost presence or absence. The transfer learning models showed significant improvements in generalization and accuracy, surpassing 95% accuracy for EfficientNetB0 and ResNet50. This demonstrates thepotential of transfer learning in remote sensing and planetary surface analysis. Despite higher precision and recall in the CNN+MLP model, the models' balanced approach minimized false positives and negatives, proving their efficacy in broad-spectrum classification tasks. Future work should expand the dataset to include a wider range of surface conditions and optimize current models through advanced neural architectures and fine-tuning.

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