CONVOLUTIONAL NEURAL NETWORK IMAGE CLASSIFICATION OF MARS-ANALOG TERRAIN: PRELIMINARY RESULTS AND IMPLICATIONS FOR THE SEARCH FOR LIFE ON MARS.

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Introduction: Habitats with a taphonomic window[1] are high priority targets for astrobiology missions to Mars [1]. However, if life existed on Mars it did not interact with its physical environment in a way that has been obvious to identify from orbit. Studying terrestrial Mars analogs can inform us of the types of features that serve as habitats with a taphonomic window on Earth, and by extension the types of features that should be sought on Mars. But what spatial resolutions are necessary to positively identify such targets?

To address the problem of establishing thresholds of identification in spatial resolution, we are assessing the ability of a deep convolutional neural network (CNN) to perform semantic segmentation (classify each pixel) on images of the astrobiologically-relevant Mars-analog environment, Salar de Pajonales (SdP), in Chile (Fig. 1A). Our aim is to discover the resolutions at which the habitats at SdP are no longer identifiable by the CNN to understand if the same types of features could be identified in salt-encrusted basins on Mars. CNNs excel at many tasks related to image analysis, including image classification [2], with modern CNNs capable of outperforming human analysts [2, 3]. Our investigation requires a consistent analysis of the same terrain over many ground sampling distances (GSDs). A single human analyst would become biased after the first classification task, and many human analysts would vary in their ability to classify a scene. Therefore, a CNN is a natural choice to tackle this problem.

Here we present initial results of the semantic segmentation of our highest resolution (3 cm/pixel) scene of SdP. In future work, we will evaluate the CNN performance at progressively lower GSDs to establish thresholds of identification for habitats at SdP.

Geologic Background and Relevance to Mars: Salar de Pajonales (SdP) is a salt-encrusted basin in the Chilean Altiplano (25°08'29"S, 68°46'20"W, 3547m, Fig. 1A) [4]. Its polyextreme characteristics make it a suitable analog for a post-Noachian martian climate [5]. Our study site within SdP is a gypsum-dominated area that notably hosts ridges and tumuli [6] that serve as endolithic habitats [5], and a "patterned ground" unit that represents a biological soil crust [5] (Table 1, Fig. 1B).

Data and Methods: We captured images of our

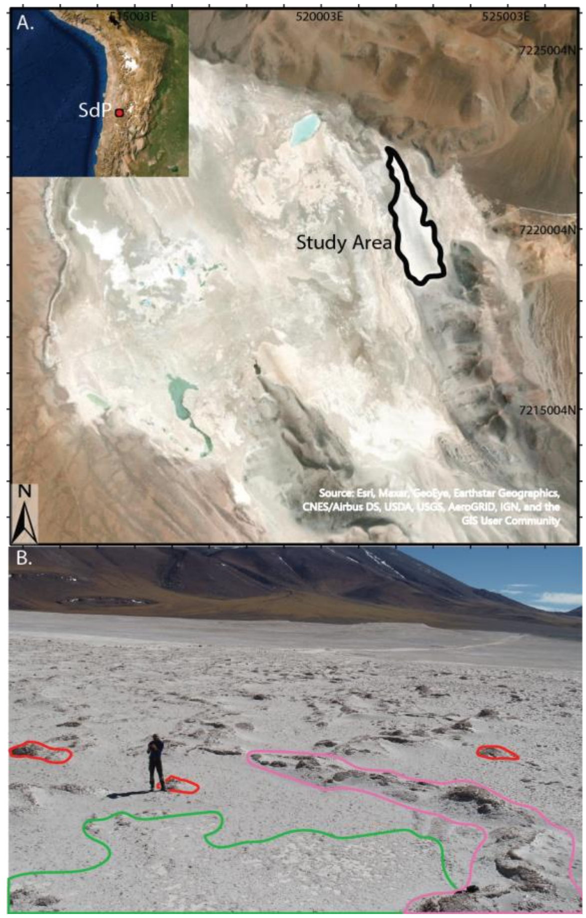

Figure 1: A. Context of SdP in S. America and location of the study area within SdP. **B.** Examples of tumuli (red), ridges (pink), and patterned ground (green).

Textural-morphological Class	Description
Patterned Ground	Centimeter- to decimeter-scale polygons of light-toned, uncovered salar surface.
Ridges	Positive topographic features with length:width values > 2:1. Typically 1-2.5 m-wide and decameters long. Can be eroded or uneroded.
Tumuli	Tumuli are circular to sub-circular positive topographic features with length:width values of ≤ 2:1.

Table 1: Descriptions of the 3 textural-morphological classes associated with microbial colonization at SdP. Colors correspond to the outline colors in Fig. 1B.

[1] Sedimentary and diagenetic circumstances conducive to preservation of biosignatures [1].

field site and surrounding terrain using a 20-megapixel camera mounted on a small unmanned aerial system (sUAS). CNNs require large volumes of data for *training*, i.e., the process of adjusting the CNN weights to optimize performance, and an independent dataset for performance *testing*. Therefore, we captured images over two non-overlapping regions of the study area for CNN training and testing. Individual image frames were processed using Pix4D Mapper into digital elevation models (DEMs) and orthophotomosaics. DEMs were combined with orthophotomosaics to make 4-band data products on which CNNs were trained and tested.

Ground truth classification of the training and testing scenes was accomplished by a human analyst with on-the-ground knowledge of the field site. The scenes were classified into 12 "textural-morphological classes" (TMCs). TMCs were based on both field experience and a visual assessment of texture and morphology in the scenes. Our results focus on the three TMCs that primarily serve as habitats at SdP: ridges, tumuli, and patterned ground [5].

Training and evaluation of the CNN. For our study, we chose to use the well-established CNN ResNet50, a 50-layer-deep residual network ideal for segmentation tasks [7]. Tools available in the MATLAB® Deep Learning Toolbox and Deep Network Designer were used to train a fully-connected version of ResNet50 with transfer learning, which carries several advantages over training a model from scratch [e.g., 2, 8]. In total, 316 images at 503x503 pixels were extracted for training from the training scene.

We evaluated the performance of the ResNet50 CNN using the Boundary F1 contour matching score [9]: BF = 2*precision*recall/(precision+recall) [see 9 for a more complete description of the calculation of BF score]. BF scores range from 0 to 1, with 0 being least and 1 being most accurate. The BF score is useful when a measure is desired that matches more closely with a human qualitative assessment than other metrics, such as the intersection over union [9].

Results: The classification map resulting from our ResNet50 semantic segmentation is presented in Fig. 2B along with a visible image of the test scene (Fig. 2A) and the analyst-derived "ground truth" classification map (Fig. 2D). The ResNet50 model performed worst on the patterned ground TMC, which received a BF score of 0.19. Ridges received a score of 0.92 and tumuli received a score of 0.71. These scores are comparable to a CNN-based semantic segmentation recently performed on HiRISE images of Mars [10].

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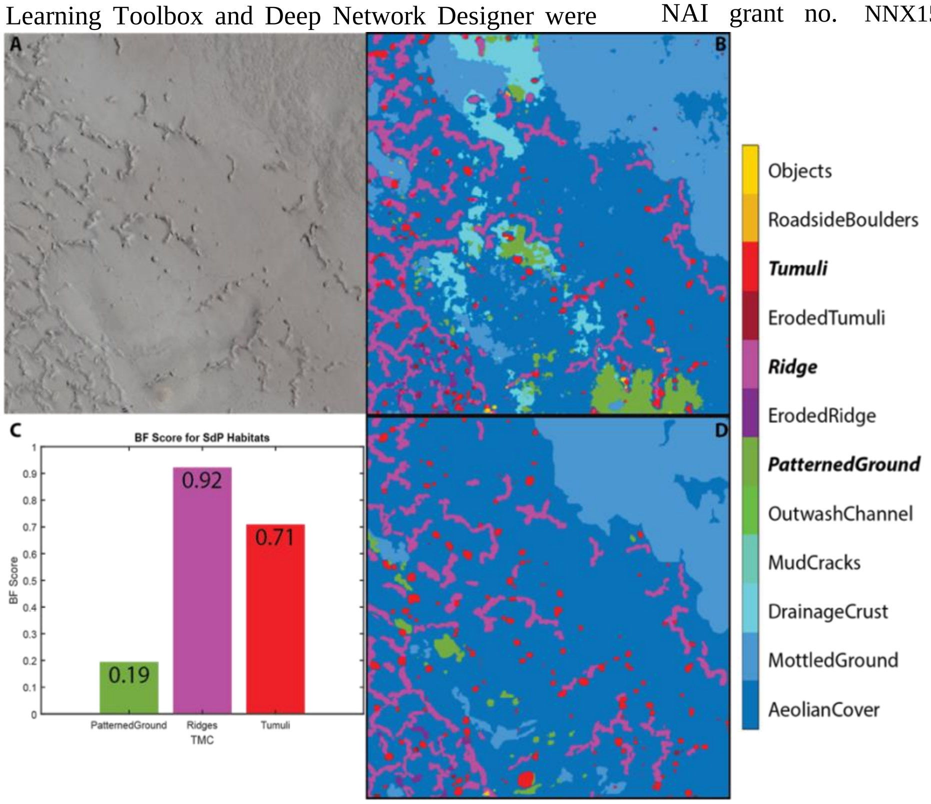

Figure 2: Summary of semantic segmentation results. **A**. Reference image of the scene used to test CNN performance. **B.** Classification map resulting from the ResNet50 semantic segmentation of the scene. Colors correspond to the bar to the right. **C.** Bar chart showing the BF score for patterned ground, ridges, and tumuli. Colors correspond to **B** and **D**. **D.** Ground truth classification map.

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