IDENTIFICATION OF MARTIAN SURFACE MINERALS IN CRISM IMAGERY USING A DEEP NEURAL NETWORK.

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Introduction: Visible and Near-Infrared spectroscopy has been used by the Observatoire pour la Minéralogie, l'Eau, les Glaces et l'Activité (OMEGA) instrument[1] and the Compact Reconnaissance Imaging Spectrometer for Mars (CRISM)[2] instrument on the Mars Reconnaissance Orbiter to elucidate the composition of the Martian surface through the detection of diagnostic infrared absorptions attributed to specific mineral compositions [3,4]. Aided by the spectral parameters formulated by [5], these instruments have observed a wide array of minerals indicative of formation in ancient Martian environments [6,7,8,9]. Typically, a CRISM image RGB composite is produced by combining three parameters, which allows for visual representation of the presence of specific mineral groups. Determining the presence of specific minerals currently involves a tedious process of generating spectral ratios, and visually comparing them to infrared spectra from mineral libraries. While this type of manual inspection is suitable for a small subset of observations, it is untenable for a global or even regional large-scale spectroscopic survey of the surface.

Automated processing of CRISM data has been previously employed in the detection and mapping of specific mineral phases. [10-13]. Implementing the use of a Deep Neural Network (DNN) to the entire CRISM dataset, a large regional-scale study, or the new MRDR map tile mosaics [14] would simplify the automation process and enhance the versatility of surface mineral research. A previous neural network approach was successfully used to determine the temperature and single scattering albedo for each pixel in a group of CRISM scenes from 1-3.8μm [15]. In a previous iteration of this study I attempted to utilize a Convolutional Neural Network to identify significant outcrops of mineral parameters from [5] but given the random shapes of outcrops and the lack of distinct patterns in parameter values, the results were not optimal [16]. For this study I construct a DNN that, unlike [16], will examine the entire VNIR range covered by CRISM (.436-3.89μm) of each pixel in a CRISM image or set of images and illuminate contributions of end-member minerals to the final spectra.

Methods: A DNN, like most machine learning applications, is an algorithm that is trained on large datasets for the specific purpose of complex pattern recognition. The DNN is trained on grouped end-member mineral reference spectra from the CRISM targeted United States Geological Survey and Minerals Identified in CRISM Analysis (MICA) libraries. The DNN is then evaluated on Map-Projected Targeted Record CRISM images. The end-member spectra present in these mineral spectra libraries have been pre-configured to account for absorption of the Martian atmosphere and are specific to Martian chemistry. The DNN is trained to classify the 31 minerals found in the MICA spectral library, in addition to 1 null class corresponding to ignored values.

Because the spectra of each pixel will contain contributions from multiple end-member minerals, the DNN will not function properly as a standard classifier, which attempts to identify one mineral that is a "best-fit" for the spectra. The DNN would need to be modified to identify the contributions of each mineral to the observed spectrum. To accomplish this, we implement a multinomial regression (Softmax) algorithm for the class evaluation which returns a decimal confidence value between 0 (No confidence) and 1 (100% confidence) for each class [17]. Confidence values of greater than .1% are considered significant contributions to spectral signature, and smaller confidence values are considered insignificant.

The CRISM image data are preprocessed for the DNN using the same method as [16]. The DNN is developed using Tensorflow in the Python

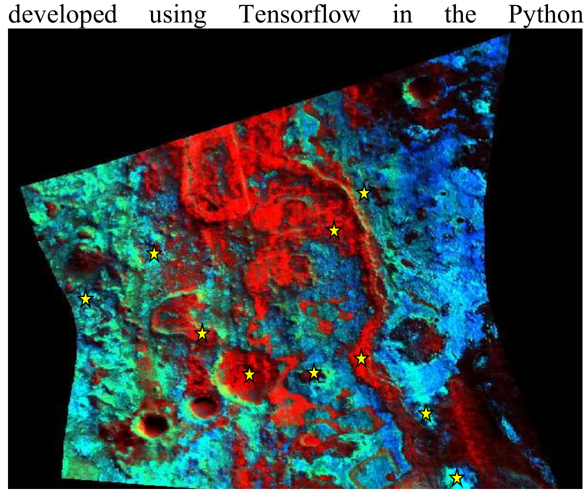

Figure 1: Preliminary results of the DNN for CRISM Image FRT00009326(Mawrth Vallis). Red corresponds to High-Calcium Pyroxene, Green to Kaolinite, and Blue to Polyhydrated Sulfates. Gold stars indicate select points for spectral assessment.

environment. The Neural Network is configured using 1 input layer containing 489 neurons (equal to the number of bands in the spectral profile), 6 hidden layers each containing 545 neurons, and 1 output layer consisting of 32 neurons (corresponding to the number of classes). The neurons utilize a RELU activation function, and the neural network is trained using the Adam Optimizer function [18].

Results from the Softmax confidence evaluation will be compared to spectral parameter products derived from [5]. Initially, the assessment will be a qualitative pattern recognition assessment. To further verify the results from the DNN, individual spectra from select pixels in the CRISM image will be evaluated and compared to the confidence values from the DNN. Select points are shown in Figure 1.

Results: The DNN performed evaluations of CRISM images in several regions previously evaluated as rover landing sites (Mawrth Vallis, Gale Crater, Jezero Crater and Eberswalde Crater). Figure 1 shows a visualization of the DNN output for select minerals in the Mawrth Vallis region. Visual comparison to browse products created using parameters from [5] is promising and shows that the DNN is capable of recognizing spectral patterns in conjunction with the geological context of the tested images [Figure 2].

Discussion and Conclusions: The results from the DNN appear to be very proficient at classifying minerals on the surface based on examining the entire reflectance spectra, rather than on a single spectral absorption, as seen in [5]. A quantitative assessment method is still being developed to better evaluate the accuracy of the DNN results against known standards, such as the parameters from [5] and results from other regional studies. There is some difficulty in this, however, since the indices in [5] are not calculating the same values as the neural network.

When properly validated, this Neural Network will be useful for analyzing the entire CRISM dataset with strong accuracy and efficiency. It could be used to produce planetwide geological maps and identify large scale geological structures. It could also be useful for resource analysis for future manned missions on Mars. Ultimately, the DNN is planned to become universal for application to multiple planetary datasets, including the Lunar Reconnaissance Orbiter, Cassini, Dawn and Bepi-Colombo.

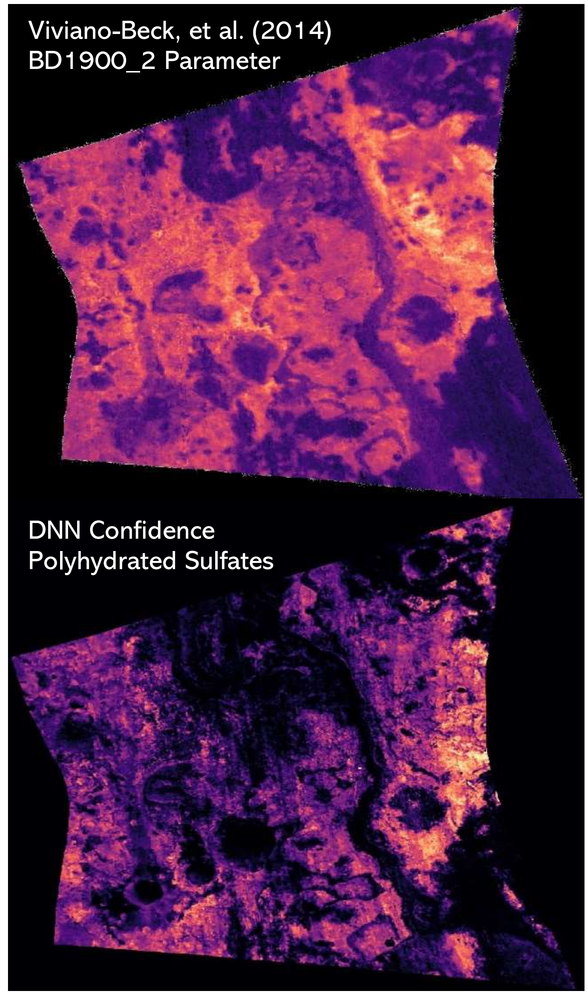

Figure 2: Visual comparison of the Viviano-Beck (2014)[5] BD1900_2 parameter [Top] with the output of the Deep Neural Network searching for polyhydrated sulfates[bottom]. The 1.9µm absorption band is significantly stronger than the 2.4µm band. Therefore using SINDEX2 produces weaker results. CRISM Image FRT00009326, Mawrth Vallis.

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