Classification of Carbonates of Mars using Machine Learning.

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Introduction: Mars is an important source for mineral exploration as it helps us in understanding complex geological processes that have happened in the past, and more recently, about the potential of life on other planets as well. The mineralogy of Mars is quite diverse, with the majority of the upper crust being basaltic in nature, and some quantities of olivine, plagioclase and pyroxene. The study of Carbonates on Mars is of crucial importance as the presence of carbonates act as a basic constituent for organic life discovered yet. Thus, automated mapping of such important minerals is an important task. Machine learning based approaches, however, have proven to be of great use for such tasks. It not only automates the entire process, but with few training samples, it is able to generalize and classify variable inputs containing noise, which is a constraint for traditional statistical based approaches.

With the use of machine learning techniques for classification of Carbonates, the task becomes more automated, accurate, and in fact with the right available training dataset,

Study Area and Dataset: The study area for this particular study is in the Nili Fossae region(Lat long). The dataset utilized is Map-Projected Targeted Reduced Data Record (MTRDR) of CRISM (Compact Reconnaissance Imaging Spectrometer) onboard MRO (Mars Reconnaissance Orbiter) as shown in Fig1 in the form of false color composite (FCC) where the wavelengths for Red, Green and Blue are 2529.51 nm, ,1329.21nm and 768.40 nm respectively, which is a hyperspectral sensor with 544 spectral bands ranging from 362 - 3920 nm. The study area was selected based on the prior studies which have shown evidence of substantial amounts of Carbonates in the given region (~22°N, 75°E).

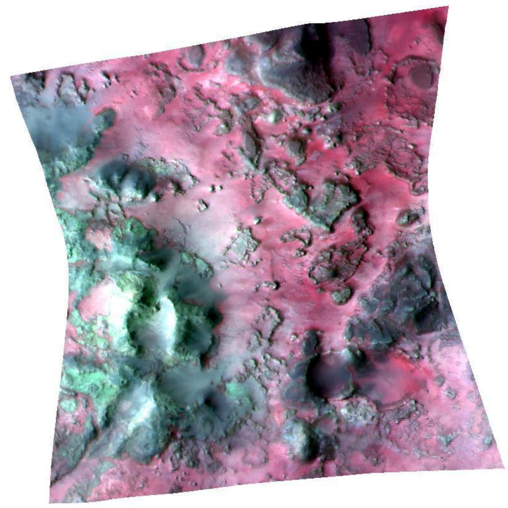

Fig1.FCC map from CRISM data of Nili Fossae region on Mars.

Methodology: Artificial Neural Network (ANN) was developed for this particular study. Training dataset were manually created based on the comparison with the CRISM Spectral library. Since the derived dataset was utilized, thus pre-processing only included bad bands removal and spectral smoothing. The training dataset included 280 pixels, which included three classes, namely none which represented the white background pixels, carbonate class which represented the carbonates, and the rest from the raster being classified as a mixture of constituents. 200 pixels were used as validation dataset, and the accuracy came out to be 90.02% for this particular area. The input data was fed to the ANN and in the output, the threshold-based probability of a pixel was yielded which classified the pixel as 0 or 1, where 0 were depicted as non-carbonate and 1 as a carbonate.

Results: In the hyperspectral derived product, sea-green color represents the highest potential carbonate regions based on the band combination chosen, and in the output through the machine learning algorithm, green color represents the classified carbonates. As observed in Fig2, it is clearly visible that a lot of area has been overlapped between the visible false color composite as shown in Fig1 and the output, where the machine learning algorithm classifies more accurately based on the accuracy metrics from the test dataset. Machine learning based techniques can be used for classification of minerals where there is little knowledge about in situ constituents. Not only a single class of minerals can be identified, but machine learning based approaches can also help in the classification of a variety of carbonates, and other minerals which are of great importance.

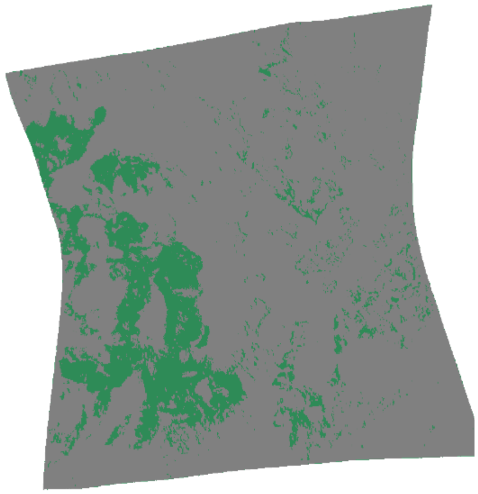

Fig2. (Output from the ANN)

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