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Application of machine learning to identify surface minerals in CRISM imagery

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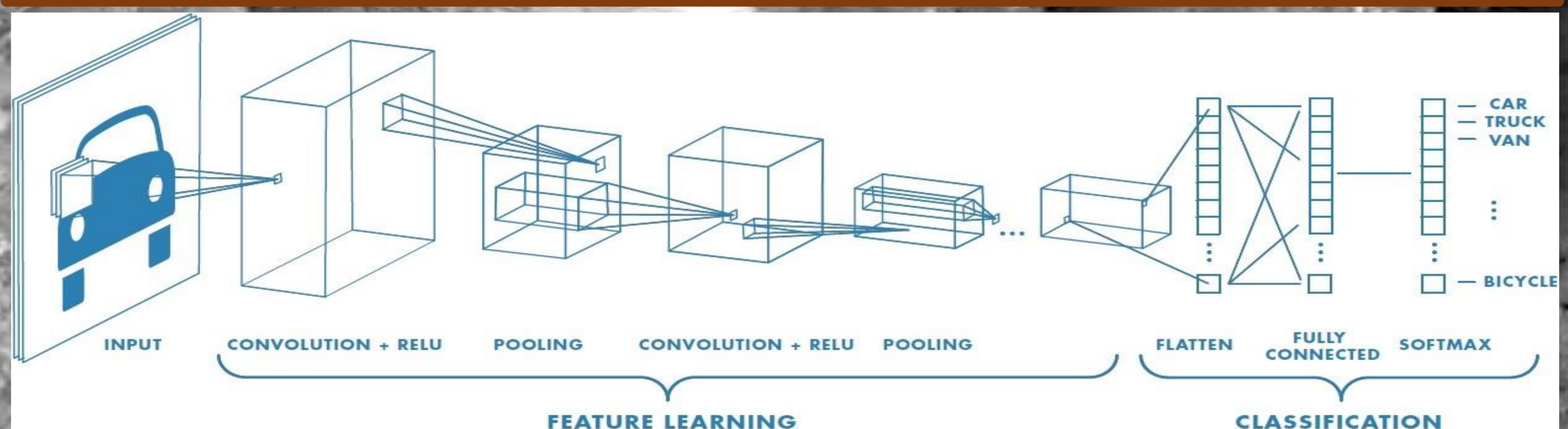
Summary:

- Applied a Convolutional Neural Network to analyze CRISM TER3 SR Image channels for strong mineral assemblages.
- Convolutional Neural Network evaluation metrics not ideal. Use of a different methodology and processing more complete CRISM file types would be more appropriate.
- With improvement, this can be applied to future research use to pre-evaluate images for existence of rare mineral phases, saving time for research.

Introduction:

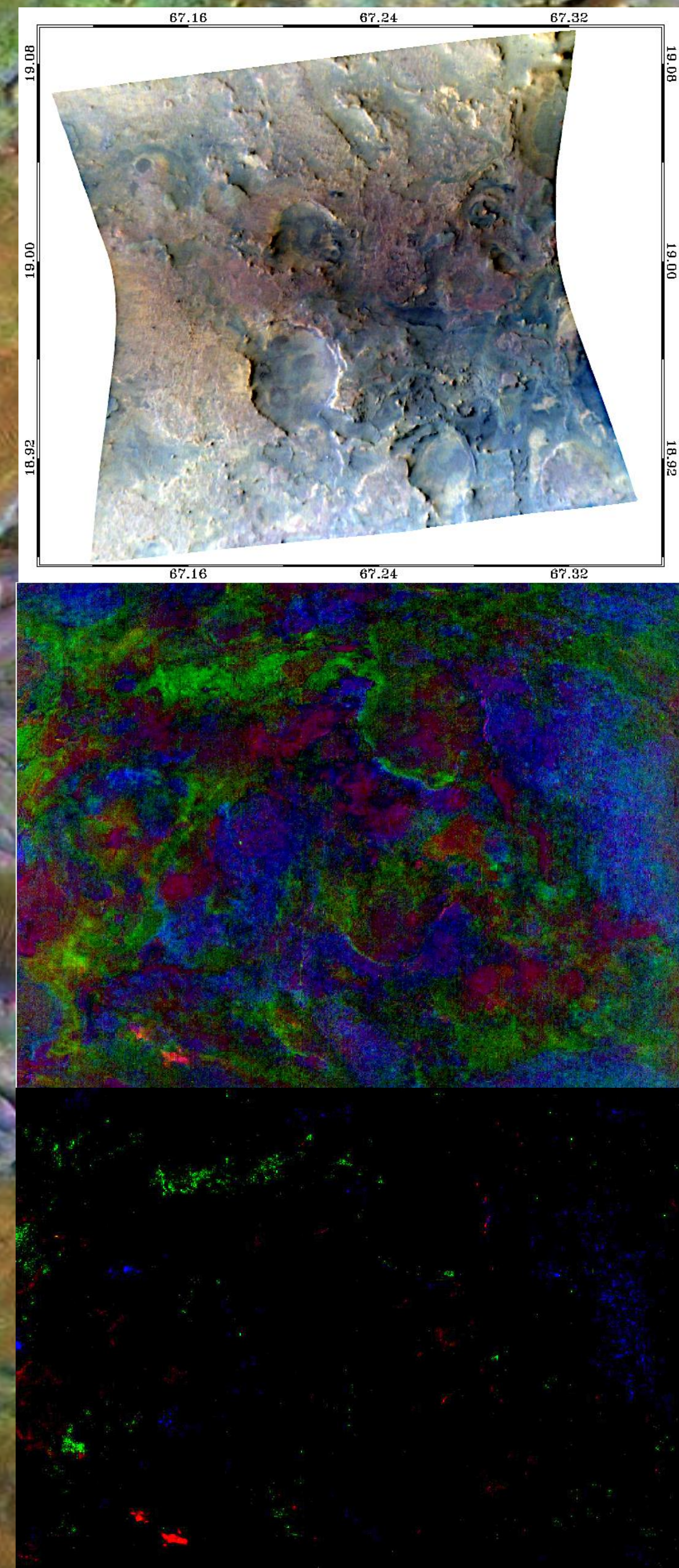
- CRISM (Compact Imaging Reconnaissance Spectrometer for Mars) was an instrument on the Mars Reconnaissance Orbiter that produced hyperspectral Visible and Infrared imagery of the Martian Surface.
- Imagery enables surface composition of Mars to be determined by comparing reflectance values with Earth-based minerals.
- Analysis of CRISM Images using the standard ENVI Software is quite time consuming and the results are subjective to the researcher's technique.
- Machine Learning techniques have been used on CRISM images to identify physical features, surface albedo and temperature.
- This study attempts to apply a Convolutional Neural Network (CNN), which is specially designed for image classification, to classify the presence of specific mineral assemblages on the Martian Surface



Illustrative example of a basic Convolutional Neural Network (CNN) structure. [17]

Methods:

- This study utilizes 18 450x640 pixel TER3 SR files, which contain 60 pre-calculated channels containing reflectance data for specific mineral assemblages.
- Each channel is considered by the CNN as an individual monochromatic "image" with 288,000 features.
- Of the 18 files used, 16 files are used for training, and 5 files are used for evaluation.
- Images were deliberately chosen with differing physical features to assess the CNN classification ability and avoid "lucky guessing." from similarly placed mineral assemblages.
- Because of the nature of CRISM data storage, a pre-processing module was built with the GDAL Python package to parse the .img files and convert the image data into a usable numpy array. The CNN was also built in Python using TensorFlow.
- An automated CRISM processor was built to scan the images and classify each channel as having strong reflectance of a specific mineral assemblage, or not. These was verified with results from A. M. Sessa, and were used as labels for CNN training and evaluation
- The CNN utilizes two respective convolution and pooling layers, which feed into the classification network. The convolution layers are optimized using an Adam Optimizer algorithm.



TOP: A visible light RGB image of CRISM image FRT0000406B (map projected). MIDDLE: The non-map projected TER3 SR version of the same image. The RGB signals represent the reflectance of 3 mineral indices [R: BD1300 (Plagioclase), G: OLINDEX3 (Olivine), B: SINDEX2 (Hydrated Sulfates)]. BOTTOM: The top 99.9 percentile of the respective reflectances for each mineral index. This implies strong evidence for a surface outcrop of each assemblage. The objective of the CNN is to identify areas of this level of relative reflectance.

Results:

- The maximum accuracy of the CNN was 70%. Average is approximately 59%.
- Confusion Matrix (below) results reveal that the model is better at determining the lack of outcrop presence rather than properly classifying outcrops. However, no group was particularly accurate.
- Attempting to increase size of dataset ultimately reduced accuracy, showing that the accuracy associated with the neural network was likely probabilistic guesswork rather than actual classification.

Confusion Matrix (120 Batch Size)	Predicted – Not Present	Predicted – Present
Actual – Not Present	52	19
Actual - Present	32	17

Conclusions and Future Work:

- Error likely due to Neural Network processing by channel, rather than processing patterns by pixel. This method is a consequence of the CRISM data type selected.
- Because each channel contains outcrops in different places, of different geometries, and of differing values, the convolutional neural network would have difficulty properly assessing the images given the CNN methodology.
- Future wok will apply a neural network to full spectrum MTRDRs to identify rare mineral phases based on patterns within each pixel value, rather than by channel.
- Data preprocessor will be designed to become more versatile to process data from other planetary missions, such as Dawn, Venus Express, or Messenger.

References:

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