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.

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 16 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. This 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.

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.

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 work 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.

Confusion Matrix (10 Epochs)  
Actual - Predicted  |  Actual: Not Present  |  Actual: Present  
---|---|---
Actual: Not Present | 52 | 19  
Actual: Present | 32 | 17  

References:

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