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Identification of Martian surface minerals in CRISM Imagery using a Deep Neural Network.

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Summary:

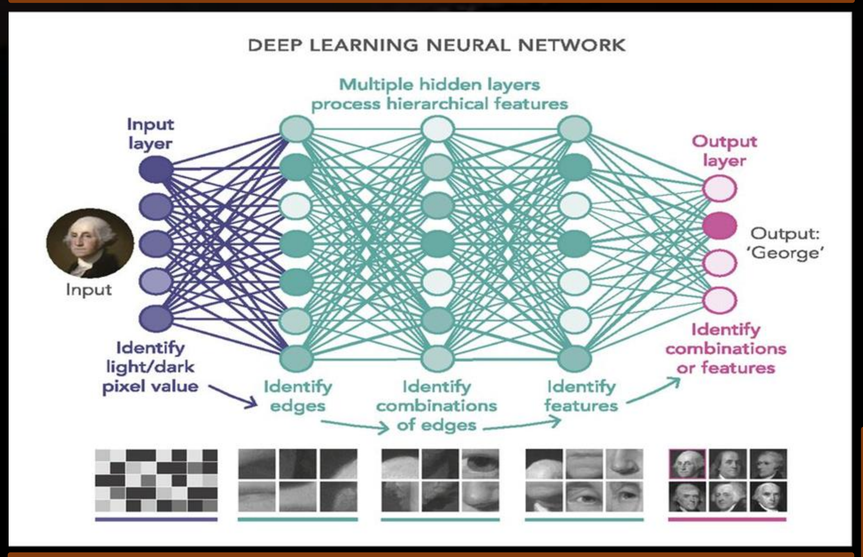
- Applied a Deep Neural Network (DNN) to analyze CRISM MTRDR IF pixel-by-pixel for presence of minerals described in MICA CRISM Library.
- Qualitative comparison of DNN results to Viviano-Beck, et al (2014) parameters shows that the DNN is good at recognizing the general regions where certain minerals are known to exist.
- Quantitative point-spectral analysis reveals

Introduction:

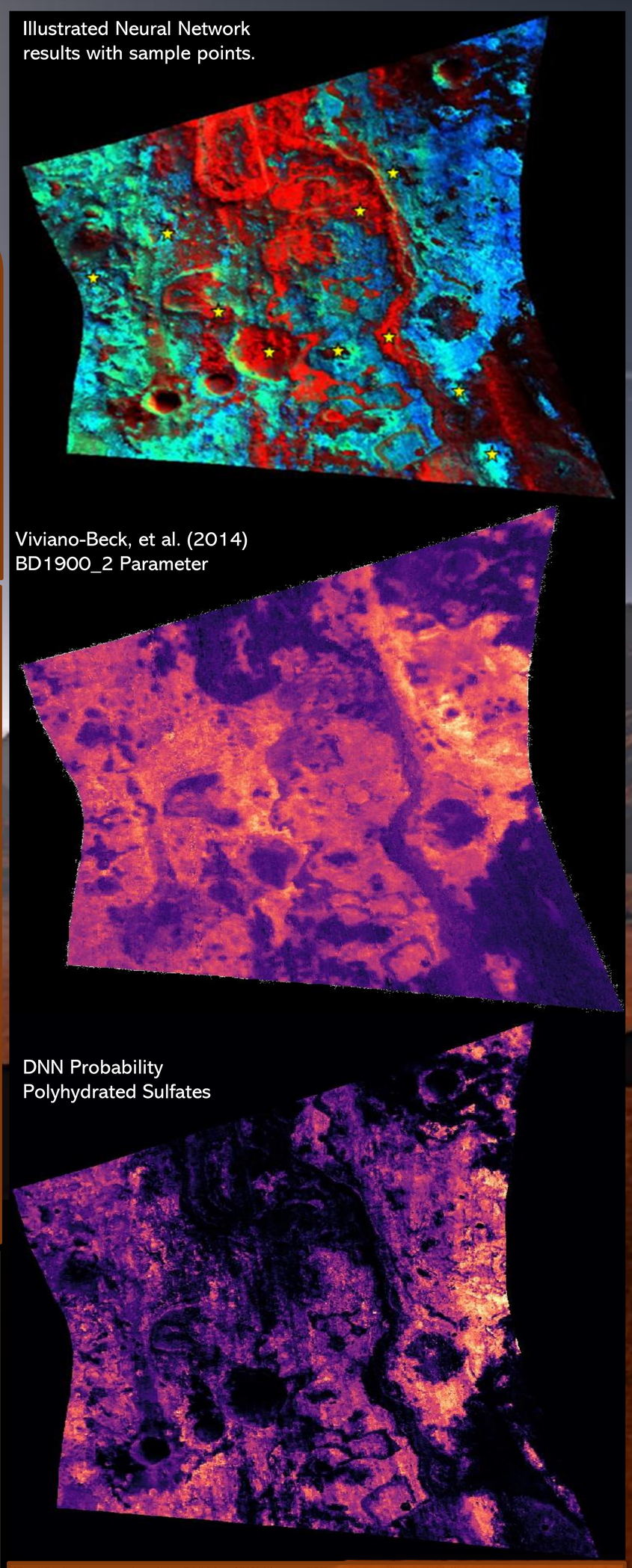
- CRISM (Compact Imaging Reconnaissance Spectrometer for Mars) was an instrument on the Mars Reconnaissance Orbiter that produced hyperspectral Visible and Infrared imagery of the Martian Surface.
- Imagery enables surface composition of Mars to be determined by comparing reflectance values with Earth-based 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 Deep Neural Network (DNN), which is specially designed for pattern-recognition and classification of large datasets, to classify the presence of specific mineral assemblages on the Martian surface.

Methods:

- The DNN is designed using Tensorflow. Consists of:
  - Input layer (489 neurons corresponding to spectral data points)
  - 20 hidden layers (358 neurons each).
  - Output layer (Contains 32 neurons, one for each of the 31 mineral classes in the MICA library, and 1 for null pixels)
  - Uses Leaky ReLU Activation Function and Adam Optimizer Algorithm
- DNN trains using MICA Spectral Library, and corresponding mineral spectra from USGS Spectral Library.
- DNN uses polynomial regression(SoftMax) algorithm, which outputs normalized probabilities of each pixel containing a specific mineral
- DNN Tested on MTRDR version of Mawrth Vallis image FRT00009326.
- Neural Network Accuracy Evaluations:
  - Qualitative comparison with Viviano-Beck spectral parameter results.
  - Point-Spectral Analysis:
    - Each library spectrum is subtracted from a sampled point spectrum(Top Figure) by band.
    - Residuals are considered deviation from the "mean" (0 = Perfect fit between curves).
    - Probability score is determined from average z-score of residuals for each mineral at each point.
    - Probabilities compared to Neural Network results.



Schematic of a Deep Neural Network algorithm modified from [17].



[Top] 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.
Visual comparison of the Viviano-Beck (2014)[5] BD1900_2 parameter [Center] with the output of the Deep Neural Network searching for polyhydrated sulfates [Bottom]. Color values are normalized to measure intensity, but not to measure exact values. The 1.9μm absorption band is significantly stronger than the 2.4μm band. Therefore using SINDEX2 produces weaker results. CRISM Image FRT00009326, Mawrth Vallis.

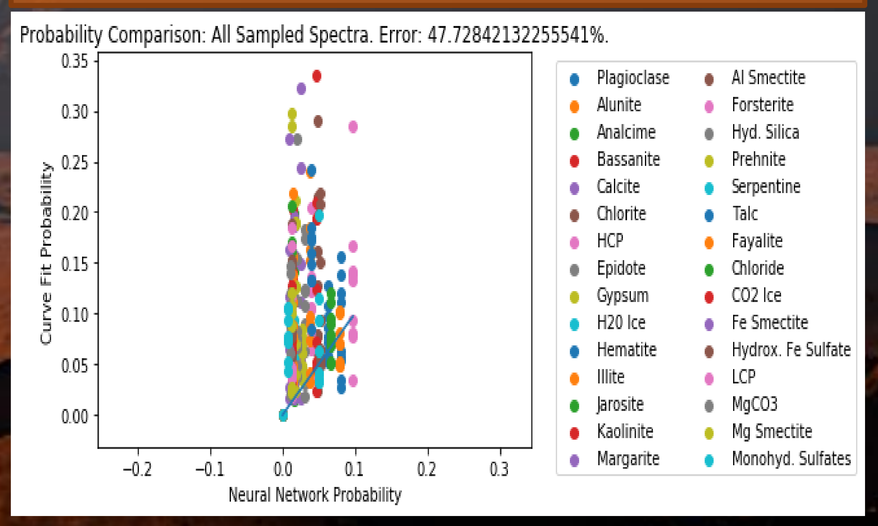
Results:

Qualitative Comparison:

- Visual qualitative comparison of the DNN results with characteristic Viviano-Beck, et al (2014) parameters indicates the neural network is proficient at finding regions within the image where the minerals in question are expected to be found. (Center figures, Center and Bottom)
- Absolute color magnitudes on figures are different:
  - Viviano-Beck, et al. (2014) parameters are measuring ratio magnitude.
  - Neural network is measuring mineral probability.
- Location-specific relative magnitudes are very similar.

Point-Spectra Validation:

- Point spectral analysis reveals a modest yet promising correlation between neural network and curve fitting probabilities.
- Graphical results (Figure Below) indicate two situations:
  - Underfitting of Neural Network (less likely).
  - Overfitting of curve fitting algorithm (more likely).
  - Most minerals in question, based on Viviano-Beck parameters, are only present in trace amounts, while only a small handful of minerals are significantly abundant.
  - The neural network appears to be erring (correctly) on the side of "Not abundant."
  - Further development of the curve fitting algorithm is necessary.



Conclusions and Future Work:

- Qualitative comparison to parameters from Viviano-Beck, et al. (2014) is promising, and demonstrates strong correlation.
- Quantitative point-spectral analysis is modest but promising and warrants further development of validation algorithm.
- Possible sources of error exist within point spectral analysis algorithm.
- Once further validation attempts are successful, the Neural Network will be tasked with evaluating the entire CRISM database and normalizing evaluations across entire planetary dataset.
- 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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