Convolutional Neural Network Models for Ordinary Chondrite Petrologic Type Classification

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Introduction: Recently, machine learning methods have seen a rise in implementation and success within the context of planetary sciences [1]. Much of this work has taken place in a geophysical context but could be implemented to great affect in the exploration subfield of planetary science. As such, in this work we begin to explore how deep neural networks can be utilized for in-situ material identification and feature detection in remote-sensing. In this work, we train a convolutional neural network capable of classifying ordinary chondrites into petrologic types based upon reflected light microscopy.

Methods:

Training Data. Reflected light images of each sample were captured using a Fein Optic microscope with a 4x objective lens and an AM-Scope MU1403 camera attachment. Individual images were collected following a rectangular grid that covered the entire thin section sample. Individual captured images were in the .png format and were collected in greyscale. Pixel values are normalized to 255 and range between 0 and 1. Individual captured images were converted into whole-section mosaic images via the image stitching software PtGUI. Generated whole-section mosaic images were output into the .tif format. Mosaic images were generated for the following samples: ALH 77221 (H4), ALH 77288 (H6), ALH 78109 (LL5), ALH 78119 (LL3.5), ALH 81017 (L5), ALH 84081 (LL6), ALH 85017 (L6), ALH 85033 (L4), ALH 85070 (L3.6), DAV 92302 (LL3.6), GRO 95658 (LL3.2), QUE 93050 (LL4), WSG 95300 (H3.3). Training set data was generated by selecting 256x256 pixel sections of each mosaic image. This was done randomly to avoid underlying biases associated with human selection. A training data set of 30,000 images was produced via this process.

Model Architecture and Training In order to build models we coded our CNN architecture in python using the tensorflow and keras packages [2][3]. For our initial model we used an architecture that consisted of two separate convolutional layers with kernel dimensions 3x3x1. Each convolutional layer used the rectified linear unit function (ReLU) as an activation and used 2x2 max-pooling dimension reduction. The output feature matrix is then flattened into a one-dimensional array and fed into a multi-level perceptron with a softmax activation. The final layer of the model has four output neurons corresponding to the petrologic types ordinary chondrites are classified under. The output values of each of the neurons are between 0 and 1 and the sum of the output layer values equals one. Model loss is calculated via the cross-entropy loss function. Training was accomplished using an NVIDIA GeForce GTX 1060 gpu. All code will be made available at https://github.com/Jordan-M-Young.

Results:

On average our model is able to achieve a fitting accuracy of ~79% after training for 10 epochs (Figure 1). Calculated loss has an average value of 0.48 after the same interval.

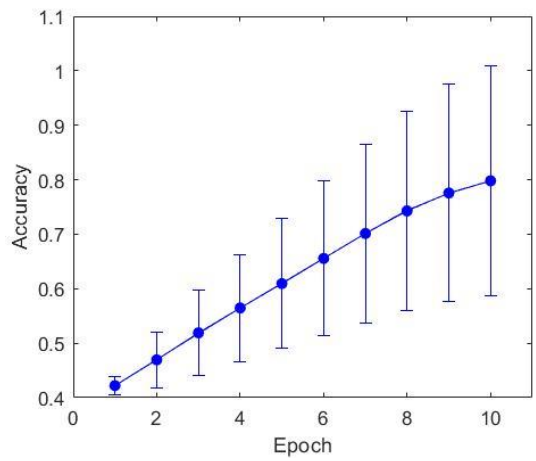

Figure 1. Average model accuracy vs. epoch; with standard deviation of accuracy; represents seven fittings.

Discussion:

A model prediction accuracy of 79% is a less than optimal result. However, addressing key factors will likely increase our resultant accuracy. First, increasing the number of unique meteorite/mosaic pairs for each petrologic type will allow the model to better understand and recognize shared petrologic characteristics between members of each petrologic type class. Second, the number of mosaic images for each class should be equivalent or the model will likely develop a prediction bias for classes that are dominant in the training data. Third it may be necessary to change the training image set size from 256x256 to 512x512 as the former may not contain enough detail regarding petrologic texture for the model to discern. Finally, addressing issues arising from the sub type classification scheme of petrologic type 3, will likely decrease model confusion.

References:

[1] Bergen, K. et al. (2019) *Science*, *363* [2] Chollet, F. et al. (2015) GitHub [3] Abadi, M. et al (2016) *$OSDI$, 16,* 265-283