EXPLORATION OF MACHINE LEARNING METHODS FOR CRATER COUNTING ON MARS. D. M. DeLatte[1], S. T. Crites[2], N. Guttenberg[3], E. J. Tasker[2], T. Yairi[1]. [1]Univeristy of Tokyo, Department of Aeronautics and Astronautics, 7-3-1 Hongo, Bunkyo, Tokyo 113-8654. [2]Institute of Space and Astronautical Science / Japan Aerospace Exploration Agency, (ISAS/JAXA), 3-1-1 Yoshinodai, Chuo-ku, Sagamihara City, Kanagawa Prefecture, 252-5210, Japan. [3]Araya Brain Imaging, Toranomon 15 Mori Building 2F, 2-8-10 Toranomon, Minato-ku, Tokyo 105-0001.

Introduction: Crater counting, a rite of passage for planetary geologists, is used to age date regions of planetary bodies such as the moon or Mars. Surface ages are determined by counting the number craters of various sizes in a region and comparing those counts to expected accumulation from a known production function based on expected meteorite accumulation rates. Radiometric dating of returned lunar samples anchor these chronologies to absolute ages [1]. For Mars, these crater counts indicate relative ages since no samples have been returned (to date). To support this method, myriad citizen scientists, graduate students, and experts have labeled – by hand – the characteristics of over a million craters. With the publication of large crater counting datasets and increased accessibility of machine learning methods and computational hardware, this historically tedious task can potentially be automated.

KerasCraterCNN: As a first step to exploring multiple methods, as a proof of concept, we repeated and extended the 2016 work of Cohen et. al. [2], who used a dataset of six Mars tiles to determine if convolutional neural networks (CNN) could determine whether a visible surface feature was a crater or a noncrater. He found, and we confirmed, that CNNs are a good tool for this purpose. Cohen et. al. used Java and a deep learning framework called Deeplearning4j to code the network. Using 10-fold cross-validation, they obtained F1-scores, the harmonic mean of precision and recall, of 88.78 to 90.29 [2], where 100 would indicate perfect identification. We obtained similar results in our implementation using Python and Keras, a high-level open source neural network API. The authors believe that the Python/Keras code will be more accessible to and reproducible for planetary scientists since Python is becoming increasingly popular in astronomy (especially as a free replacement to IDL), and Keras is a heavily tested industry standard with a broad user base.

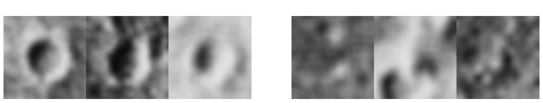

Fig. 1: Examples of craters (left images) and noncraters (right images), created using annotations and data from [2-4].

Segmentation: While the convolutional neural networks applied in KerasCraterCNN were effective for identifying craters vs. noncraters, segmentation is a potentially more flexible machine learning approach. Segmentation is a technique that starts with an image and produces an image of the same size with uniform colors identifying the objects of interest. (Ideally, the network returns an image similar to the “target” image in Fig. 2 and Fig. 3.) This technique has been used in other research areas such as autonomous cars and biological cell segmentation [5]. Our use of the segmentation approach for crater counting facilitates a new attempt to extend the work above beyond crater/noncrater identification to determining radius and location of craters. Using complete images instead of pre-chosen sections (Fig. 1) raises the difficulty for the network but is closer to the experience of human crater counters.

Early results from segmentation of craters were mixed. Robbins & Hynek’s Mars > 1 km annotations [6] are used in conjunction with the THEMIS Daytime IR images of Mars’s surface [7]. Challenges in the dataset included overlapping craters, craters within craters, and the single color channel. The single color (grayscale) means there is only one third the data to “learn” from compared to a color image with three channels (red, green, and blue). Missing data in the THEMIS images (shown as empty/black pixels) reduced the effectiveness and accuracy of the results; some labelled craters resided entirely or mostly within missing pixels.

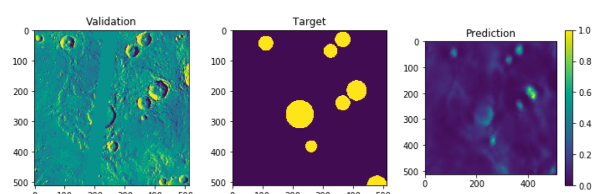

Fig. 2: Example of crater extraction in 4-16 km range.

Synthetic data: To understand which factors most heavily influenced the performance of the segmentation neural network, the authors embark on a series of experiments with synthetic data to determine the major causes of inaccuracies in the final segmentation results. Experiments test the impact of crater density, variety of crater sizes, and crater background on the network's ability to create the segmentation map.

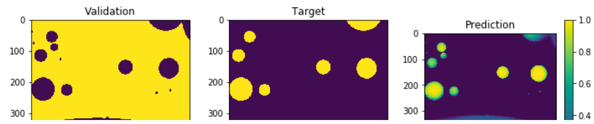

Fig. 3: Example of the simplest type of synthetic data. Network is extracting craters in a range of diameters.

Future work: Once the synthetic datasets are created and tested, they will be used to help train the segmentation network with the aim of improving the results of running the algorithm on unseen data. Other machine learning algorithms will be explored and the results compared with segmentation networks.

References: [1] Crater Analysis Techniques Working Group (1979) *Icarus, 37,* 467–474. [2] Cohen, J. P. et. al. (2016) *LPS XLVII,* Abstract #1143. [3] Urbach, E. R. and Stepinski, T. F. (2008) *LPS XXXIX,* Abstract #2184. [4] Bandeira, L. et. al. (2010), *LPS XLI*, Abstract #1144. [5] Ronneberger, O. et al (2015) *MICCAI,* 234–241. doi:10.1007/978-3-319-24574-4_28. [6] Robbins, S. J. and Hynek, B. M. (2012) *JGR: Planets, 117,* doi:10.1029/2011JE003966. [7] Mars Global Data Sets (2006). *THEMIS Day IR Global Mosaic.* http://www.mars.asu.edu/data/thm_dir/