Deep learning to detect Lunar craters and transfer-learn to Mercury. A. Silburt$^{1,2,3}$, M. Ali-Dib$^{4,5}$, C. Zhu$^{4,6}$, A. P. Jackson$^{1,7}$, D. Valencia$^{1,8}$, Y. Kissin$^{9}$, D. Tamayo$^{1,4}$, and K. Menou$^{1,4}$, $^1$Centre for Planetary Sciences, University of Toronto at Scarborough, Toronto, Ontario M1C 1A4, Canada; $^2$Department of Astronomy & Astrophysics, Penn State University, Eberly College of Science, State College, PA 16801, USA; $^3$Department of Astronomy & Astrophysics, University of Toronto, Toronto, Ontario M5S 3H4, Canada; $^4$Canadian Institute for Theoretical Astrophysics, 60 St. George St, University of Toronto, Toronto, ON M5S 3H8, Canada; $^5$School of Earth and Space Exploration, Arizona State University, 781 E Terrace Mall, Tempe, AZ 85287-6004, USA. Corresponding authors: A.S. (ajs725@psu.edu), and M.A.-D. (m.alidib@utoronto.ca).

Introduction: Crater counting on the Moon and other bodies is crucial to constrain the dynamical history of the Solar System. This has traditionally been done by visual inspection of images, resulting in human generated databases that are either spatially comprehensive but restricted to large craters, or size comprehensive but limited to a specific geographic region. Convolutional Neural Networks (CNNs) are a widely used deep learning method, particularly effective for classifying images and other data with correlated features.

In this work we train a CNN implementation using a composite lunar crater dataset. Our automated method is fast, accurate, and can detect craters on other bodies without the need for retraining.

Methods: We generate our dataset by randomly cropping images from the Lunar Reconnaissance Orbiter (LRO) Lunar Orbiter Laser Altimeter (LOLA) Kaguya merged digital elevation model (DEM). Our version of this DEM has a resolution of 256 pixels/degree (118 m/pixel). We split the data into 3 equal sized training, validation, and testing sets spanning respectively 180° to -60°, -60° to 60° and 60° to 180° in longitude. Each dataset contains 30,000 images.

For our ground-truth locations and radii of craters, we merge two datasets generated by humans: the 5-20 km global crater dataset assembled by Povilaitis et al. (2017) [1] using the LRO Wide Angle Camera (WAC) Global Lunar DEM at 100 m resolution [2], and secondly the > 20 km global crater dataset assembled by Head et al. (2010) [3] using the LOLA DEM with a resolution of 64 pixels/degree (472 m/pixel).

We use a CNN in a UNET architecture [4], where the input consists of an image with NxN pixels, and the training target (output) is an image of the same size but with binary rings delimiting the craters boundaries. We are hence mapping the original input image into another image where the pixel values are 0 everywhere except the edges of the craters. Our CNN architecture is shown in Fig. 1.

Finally, we use a customized crater detection algorithm based on the “match_template” method from scikit-image to extract the longitudes, latitudes and radii of detected craters from the output targets.

Our best model is trained on the training set for 4 epochs with a batch size of 8 using the ADAM optimizer (Kingma and Ba, 2014 [5]) with backpropagation. We tune the hyperparameters of our model and crater detection algorithm on the validation set. We then use our trained and optimized CNN to generate predictions on test set images.

Results: We recover 92% of craters from the test set and double the number of total crater detections, including over 2,500 between 3-5km in diameter. Our fractional longitude, latitude and radius errors are typically 15% of its ground-truth radius, representing good agreement with the human-generated datasets. From a manual inspection of 50 CNN-predicted targets we estimate our false positive rate to be 1.9%. In Fig. 2 we compare our CNN-detected craters to the test set ground-truth for a large patch of the Moon.

We have also tested our trained model on the MERCURY Surface, Space ENvironment, GEochemistry, and Ranging (MESSENGER) global DEM of Mercury at 64 pixels/degree (665 m/pixel). We find that our model transfers well without any retraining, detecting a large fraction of the craters in each image. From a sample of 50 random images of Mercury we estimate our false positive classification rate to be 2.7%.

We demonstrate that deep learning is a viable method for detecting and counting craters, even when using incomplete human-generated ground truth datasets to train. With further improvements we are hopeful that a single CNN can perhaps be used to extract craters from all cratered Solar System bodies including the Moon, Mercury, Mars, Ceres, and Vesta, facilitating a consistent, accurate and reproducible analysis. Unlike humans, a CNN will classify an image identically each time, and takes only a few hours to extract a crater distribution from thousands of images. This is done passively, freeing the scientist to do other tasks.

We make our code publicly available at https://github.com/silburt/DeepMoon.

Fig. 1. The architecture of our UNET-based Convolutional Neural Network.

Fig. 2. Image patch of the Moon (left), craters detected by our CNN and detection pipeline (middle), and human-counted craters from our test set (right).