

**CAN WE CREATE A NEW VIEW OF THE MOON WITH MACHINE LEARNING?** G.K. Benedix<sup>1,2</sup>, A. Lagain<sup>1</sup>, and P.A. Bland<sup>1</sup>, <sup>1</sup>Space Science and Technology Centre, School of Earth and Planetary Science, Curtin University, Perth, Western Australia, Australia. ([g.benedix@curtin.edu.au](mailto:g.benedix@curtin.edu.au)), <sup>2</sup>Planetary Science Institute, 1650 E Fort Lowell Rd, Tucson, AZ 85719, United States.

**Introduction:** In recent years, Machine Learning has progressed to the point where object recognition and detection of digital images has become as (statistically) reliable as manual detection. This has led to several interesting breakthroughs regarding how other planetary surfaces can be rendered for visual inspection. [1-3]

Our group focused on the creation of a crater detection algorithm by using a combined set of open access programs pieced together such that we can analyse the highest resolution images of Mars and the Moon [2,4,5]. This algorithm is not generic, it has to be trained for each specific planetary body, but once that is done, we have a database of craters to the smallest diameter ranges detectable in the images. For Mars, that resulted in a database of ~94million craters with diameters down to 50m [4]. There is no need to use the machine learning to count the craters larger than 1km because that database has been produced manually [6,7]

This algorithm is used to augment and enhance crater counting techniques and we have used it to locate the source craters of two different groups of martian meteorites [4,5]. This was accomplished in part because of the ability to visualize the entire dataset which provided a way to pinpoint relevant craters of interest, narrowing the field of potential source craters from 70,000 to 19. [4].

Here we will show the results of the algorithm we have retrained and applied to the Moon [3] to visualize the region around the Apollo 12 landing site. We chose this area for two reasons. It has been extensively mapped already with lots of crater counting ages determined, that can be verified with samples [8,9]. And it also allows us to test how the machine learning results might be able to identify geologic units based on crater densities.

**Data and Results:** We chose an area around the Apollo 12 landing site (fig 1) that closely overlaps the area mapped by [9]. The machine learning algorithm was applied to NAC images from the LRO mission [3]. The algorithm also took, as input, the Kaguya global lunar mosaic over the Apollo 12 landing site region. Details of the algorithm are found in [3].

Our focus here is on how to use the results to maximum value. We present several visualisations of the area using the results of the algorithm over an area 8 x 9° centered on the Apollo 12 landing site

(bounding North is 1°N, South is -8°S, West is -28°W and East is -20°W). There are 679,026 craters ranging in diameter from 20m to 7.5km. This dataset was divided into diameter ranges that correlate to the root 2 bins used in crater counting chronologies. However, our focus here is the distribution of the craters. Figure 1 shows a reproduction of the Apollo 12 map (1b) produced by [9] along with the LROC WAC image of the landing site region (1a). Fig 1c illustrates the distribution of craters by diameter ranges for 3 size ranges – 1 to 8 km, 354 to 500m, and 125 to 177m. Figure 1d shows the crater density in 0.1° x 0.1° grid squares for the same diameters as shown in 1c.

Comparing the crater distribution and crater density maps to the LROC and geologic map is very interesting. First it is noteworthy that the geologic features are not visible with the data between 1 and 8km, but when smaller crater sizes are plotted, we start to see features that correlate with the optical and geologic maps. The features start to appear at diameters less than 500m, but are particularly clear between 125 and 177m, where the Lansburg crater stands out and the Imbrium Fra Mauro material is easily identified as having a lower crater density.

This is a promising use of the large datasets that can (and will) be generated using machine learning techniques. These visualisations open up a new view of Moon as well as other planetary bodies. Future work will expand the use of machine learning to identify other features of interest that can be built into a broad geologic mapping method.

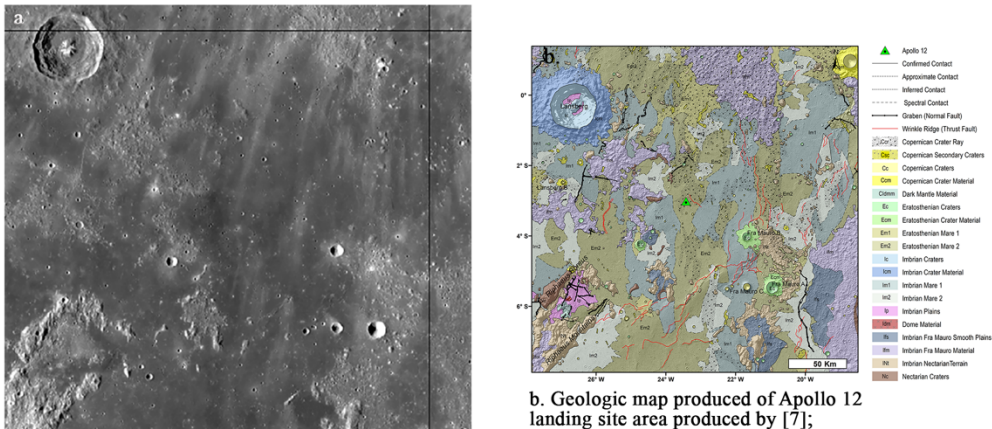
**Acknowledgments:** Apollo 12 landing site image was extracted from JMARS from the included LROC WAC global mosaic of the moon. The Crater Detection Algorithm results were manipulated using the TOPCAT software package for astronomical datasets (<http://www.star.bris.ac.uk/~mbt/topcat/>) [10].

**References:** [1] DeLatte, D.M. et al. (2019) *Adv Space Res* doi:10.1016/j.asr.2019.07.017. [2] Benedix, G.K. et al. (2020) *Earth Space Sci* 7. doi:10.1029/2019ea001005 [3] Fairweather, J.H., et al. (2022) *Earth Space Sci* 9. doi:10.1029/2021ea002177. [4] Lagain, A. et al. (2021) *Nat Comm* 12, 6352. doi:10.1038/s41467-021-26648-3. [5] Lagain, A. et al. (2022) *Nat Comm* 13, 3782. doi:10.1038/s41467-022-31444-8. [6] Robbins, S.J., (2019) *JGR Planets* 124, 871 892 doi:10.1029/2018je005592 [7] Robbins, S.J., and Hynek, B.M. (2012) *JGR Planets* 117,

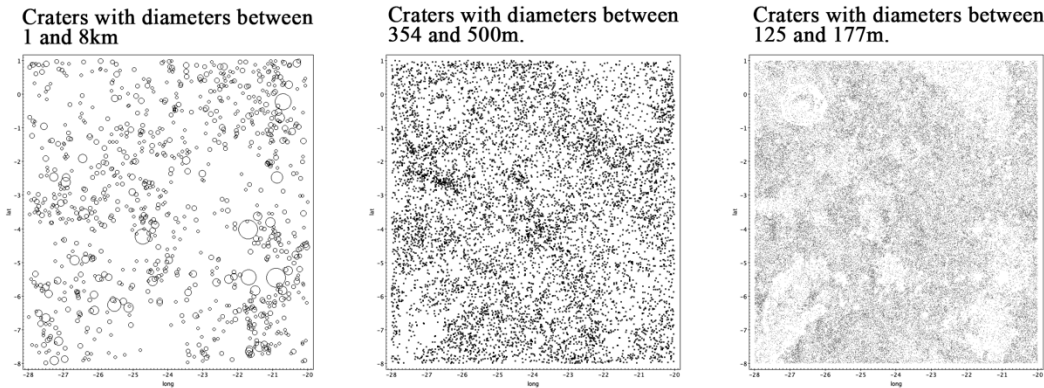
doi:10.1029/2011je003966 [8] Hiesinger, H. et al. (2012) *JGR Planets* 117, doi:10.1029/2011je003935 [9] Iqbal, W. et al. (2020) *Icarus* 352, 113991. <https://doi.org/10.1016/j.icarus.2020.113991> [10]

Taylor, M.B., (2005) TOPCAT & STIL: Starlink Table/VOTable Processing Software 347, 29.

Figure 1. All images below show the same Apollo 12 landing site area. Bounding latitude between 1°N and 8°S, bounding longitude between 20°W and 28°W.



c. Distributions of craters by specific diameter range, illustrating potential for geologic mapping.



d. All crater density images shown below are the number of craters per 0.1° x 0.1° grid spacing

