Crater Counting Using Machine Learning. G.K. Benedix[1,4], K. Chai[2], S. Meka[2], J. Paxman[3], M.C. Towner[1], A. Lagain[1], P.A. Bland[1,4] and C. Norman[3], F. Cary[5] and J. Fairweather[5]. [1]School of Earth and Planetary Sciences, Curtin University, GPO Box U1987, Perth, Western Australia, 6845, Australia (g.benedix@curtin.edu.au), [2]Curtin Institution of Computation, Curtin University, GPO Box U1987, Perth, Western Australia, 6845, Australia, [3]School of Civil and Mechanical Engineering, Curtin University, GPO Box U1987, Perth, Western Australia, 6845, Australia. [4]Western Australian Museum, Locked Bag 49, Welshpool, WA, 6986, Australia.

Introduction: Crater counting provides a relative timeline of the geological history of a planetary surface [1]. If an absolute age can be accurately attributed to a surface, the crater counting timeline can be calibrated, providing specific age information for a variety of features. This is available for the moon due to the known locations of the Apollo samples [1].

The accuracy of a determined age by crater counting is dependent on the ability to discern all the craters in a given region. Over the last 50 years, the spatial resolution of planetary surface datasets acquired by orbiting spacecraft has been improving and we can now see the surfaces of other planets at sub m scales. This level of resolution has opened up a new way to refine the ages of surfaces. But current crater counting techniques rely on individual manual counts. For Mars and the Moon, there are databases of manually counted craters [2, 3] down to a minimum size of 1km. The ability to make full use of the available high definition imagery datasets, and count crater sizes to 10s m diameters, would allow determination of the most recent resurfacing episode. But crater number scales as a power law. Those datasets are many orders of magnitude larger – inaccessible to manual counting. To access them we need to automate the process.

A number of studies have addressed automated crater detection [4]. None have achieved the ultimate goal of counting and measuring craters in a reliable and timely fashion. Approaches include edge detection, Hough transforms, and now applying Machine Learning. Although progress has been made, it is surprisingly difficult to teach a computer to recognize the subtle variation in crater morphology and sizes as a common landform, and count and characterize them. This is especially true for Martian craters because of the plethora of morphology types they exhibit. No automated crater counting study has yet progressed to the point where data output has been used to deliver geologically meaningful information

In previous work we described our technique, using supervised machine language, [5,6] in some detail. Here we discuss the evolution of the technique. We also show that results are indistinguishable from manual count datasets for craters >1km in diameter, and that the algorithm is able to recognize craters down to 10s of m across on Mars, allowing us to generate isochrons for surfaces on Mars (or any other cratered planetary surface using appropriate training sets), at ultimate resolution, routinely.

Machine Learning: Crater counting can be considered more generally as an object detection task. As such, our initial work to develop a crater detection algorithm (CDA) [5,6] began with training a convolutional neural network (CNN) using the OverFeat architecture [7] designed for object detection. However, ongoing advances in machine learning have produced newer, faster and more accurate object detection methods. In this work, we improve upon our initial CDA model by training a CNN using the state of the art You Only Look Once (YOLOv3) architecture [8].

Approach. We used 16 THEMIS Day IR mosaics (https://astrogeology.usgs.gov/maps/mars-themis-controlled-mosaics-and-preliminary-smithed-kernels) [9-12] spanning a band of Mars between -30˚ and 30˚ latitude as our dataset. The mosaics were cropped into tiles (960x960 pixels) and the Mars Crater Database (MCD) [2] was used to label the tiles with human identified crater locations. A YOLOv3 CNN model was then trained on a dataset comprising of 2,490 tiled images for 40,000 iterations with a 0.001 learning rate that achieved average loss of 0.196. The trained model was tested on a unseen hold-out dataset consisting of 1,066 images and achieved 90% precision, 94% recall, 70% intersection over union (IoU) and a mean average precision (mAP) of 90%.

The total processing time taken by our CDA method for processing a THEMIS mosaic (26,674 x 17,783 pixels) and running the detections on a GPU is ~5 minutes. A script to visualize the CDA results was also developed which has a larger execution time of ~10 minutes as it involves drawing an overlay (boxes around craters) on the tiled images and merging all the tiles back into a single mosaic image.

Results and Discussion: Initial results of the automated CDA are extremely encouraging considering the median ratio of craters counted (CDA/MCD) of all 16 mosaics is 0.95. As a case study, we have compared, in detail, the Iapygia and Elysium THEMIS Day IR mosaics. The Mars Crater Database lists 19,976 craters in the area of Iapygia (-30 to 0N;135 to 180E); our CDA counted 18,980 craters. But importantly, it is not just that the CDA counted roughly the same number of craters, but that the Crater Size Frequency Distribution (SFD) and the subtle structure within the SFD are virtually identical. Figure 1a shows where these plot on a Hartmann diagram, demonstrating that the two datasets span the same set of isochrons. The entire Iapygia surface (the area of the whole quadrangle) is between 3.5 and 4Ga in age. Figure 1b shows the comparison SFDs for the Elysium quadrangle. Elysium has fewer craters overall and thus should be a younger surface compared to Iapygia. The data in the SFD fall between the 1 and 3.5Gy isochrons, and are a good match to previously manually generated data.

These results are encouraging, because we have yet to introduce new training of more complex datasets to characterize and identify all the different types of craters (simple, complex, degraded, secondary, etc.). In addition, little extra training will be needed before applying it higher resolution image datasets to allow access to craters (and dates) down to m-sizes. This extra training will be the focus of the current activities, allowing us to apply the CDA to smaller craters (sub-km) in the CTX and HiRISE datasets.

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(https://www.psi.edu/epo/isochrons/chron04b.html)

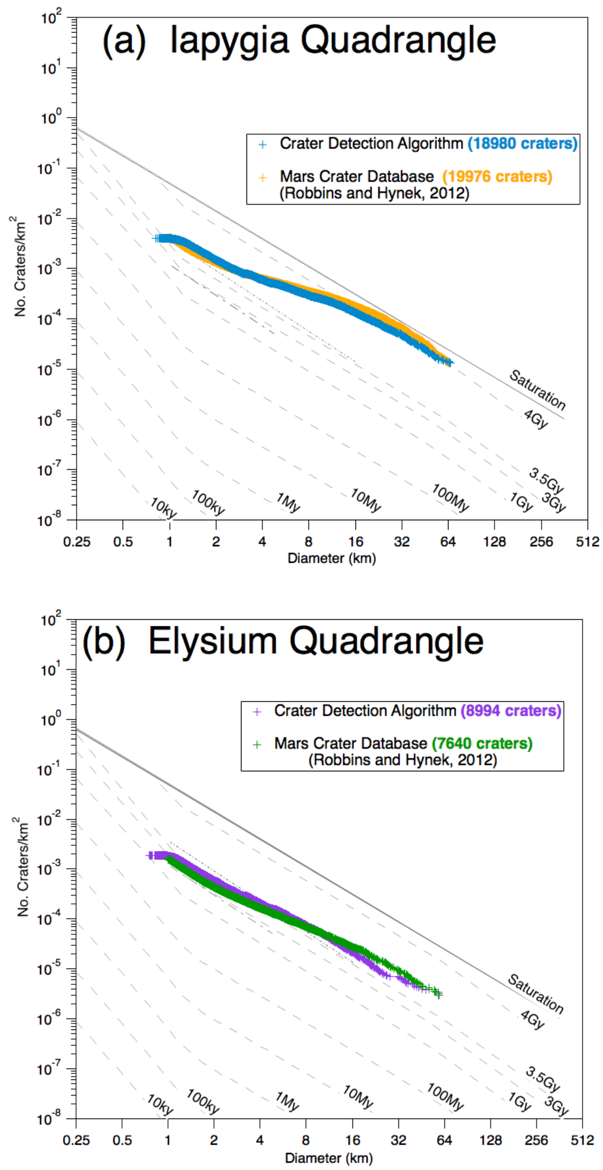

Figure 1. Crater Size Frequency Distribution comparing crater counts from the MCD [2] to results of our Crater Detection Algorithm for the (a) Iapygia and (b) Elysium Quadrangles on Mars. The isochrons are reproduced from the 2004 iteration as described by Hartmann[13].