



Exploration of Machine Learning Methods for Crater Counting on Mars



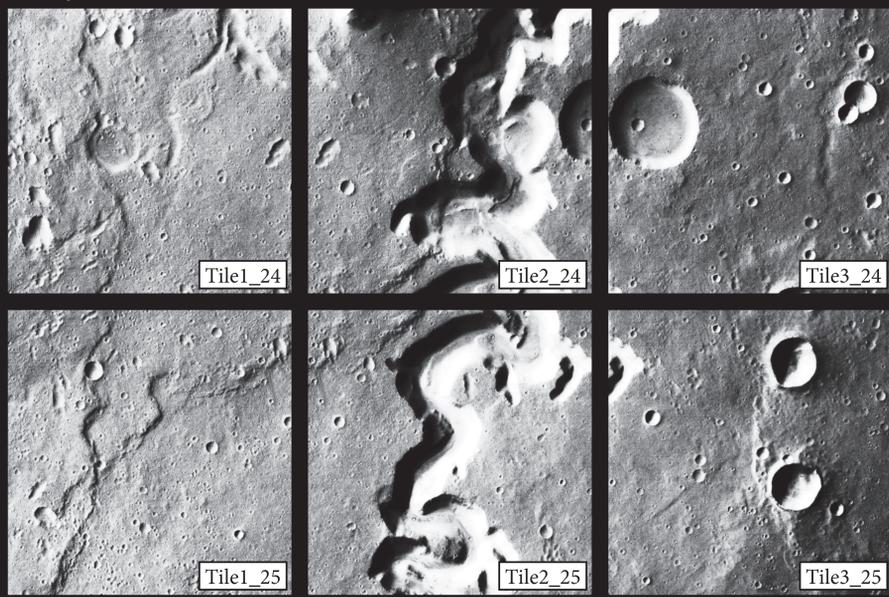
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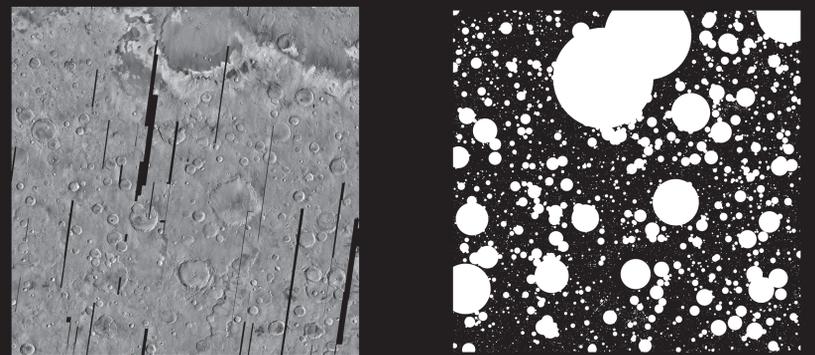
Introduction

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 of 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.

Can you count all the craters in these tiles?



Mars in the Mid-Latitudes

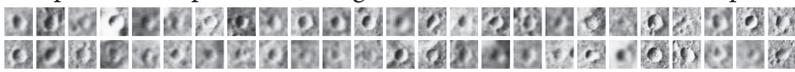


Left: Original data from THEMIS Day IR (1 of 24 tiles used) [7]
Right: Segmented craters (generated using data from Robbins et. al. [6])

Results: KerasCraterCNN

This is an implementation of Cohen's CraterCNN [2] architecture. Unlike the original, it is written in Python using Keras instead of Java using Deeplearning4j. Performance is compared to both Cohen's and others' previous work.

Example crater input data (in algorithm, all are resized to 15x15 pixels):



Example noncraters:



Below, the table shows a comparison of several algorithms [2-4] using the same metric (F1 score and 10-fold cross validation) to compare results. This table extends a table reported by Cohen [2] and adds the new results in the last column. Based on the results, the CNN structure is successfully implemented using Keras and Python.

COMPARISON OF ALGORITHMS (USING F1 SCORE * 100) ON THIS DATASET

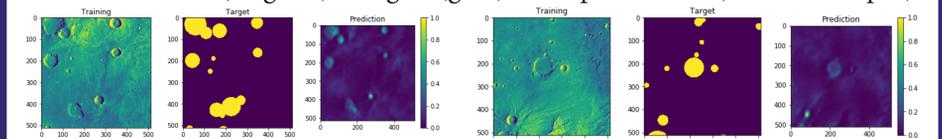
Region (match with tiles above)	Urbach 2009	Bandeira 2010	Ding 2011	Cohen 2016	KerasCraterCNN
West (1 24+1 25)	67.89	85.33	83.98	88.78	90.23
Center (2 24+2 25)	69.62	79.35	83.02	88.81	89.10
East (3 24+3 25)	79.77	86.09	89.51	90.29	93.14

Conclusion & Future Work

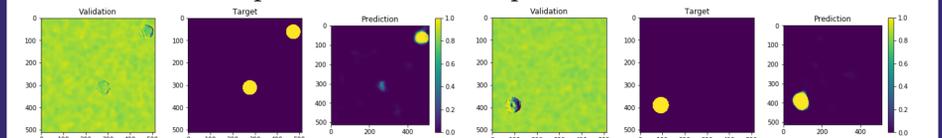
This work implemented a successful crater/noncrater convolutional neural network using the Keras framework and described a test campaign that successfully diagnosed the error in our implementation of a segmentation UNet. These results overall show the potential for neural networks to contribute to crater counting research by decreasing the amount of tedious hand labeling. Machine learning effectiveness is proportional to the quality and quantity of data. Working with larger datasets like Robbins et. al. [6] can produce enhanced results. While KerasCraterCNN requires crater examples to be suggested to the network individually, the UNet architecture shows promise for being able to present whole images to the network. Future work aims to produce automated crater counts and assess their accuracy.

Results: Segmentation Experiments

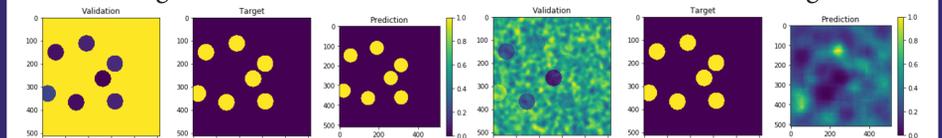
Using a UNet [5] to segment the craters initially had mixed results. Some craters were segmented well; others were not detected at all. All images below have "validation" (original), "target" (goal), and "prediction" (network output).



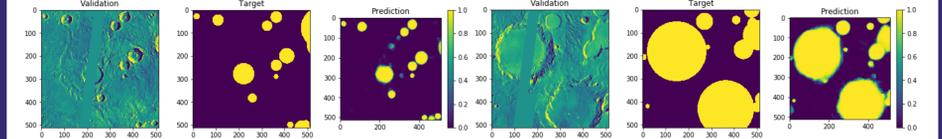
Embarking on a variety of experiments using both real craters and synthetic data indicated a few potential clues for the poor initial results.



>> Detecting craters was harder when craters were close to the average color.



>> Dot transparency was a significant barrier in some synthetic data, leading to the realization that we needed to choose a different activation function.



>> Changing each layer's activation function to ReLU fixed the problem.

>> The network was even able to identify craters despite incomplete data.

References

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6. Robbins, S. J. and Hynek, B. M. (2012) *JGR: Planets*, 117, doi:10.1029/2011JE003966.
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