



## Automatic Candidate Generation of sub-km Craters on Mars

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Crater size-frequency distributions are used widely for dating the surface of Mars [1],[2]. This currently requires an expert to manually digitise and label every crater in a given region. Crowdsourcing initiatives show some promise in reducing the workload of experts, with projects such as MoonZoo providing expert-level performance [3]. However, although the time spent by researchers may be reduced, there is a significant delay between starting a crowdsourcing campaign and obtaining the results. Attempts to automate this process in the pursuit of greater speed have suffered from errors of omission, which cannot be corrected quickly because of the need to search the image for missed craters. Therefore, there is a need to automate candidate generation in such a way that errors of omission are negligible. We present a state-of-the-art crater detection algorithm using unsupervised deep learning and a supervised Random Forest [4], that performs better than previous pipelines on the same dataset [5],[6], and shows robustness to previously unseen terrain. This algorithm can be quickly trained on an existing dataset (available at [github.com/iee8023/CraterDataset](https://github.com/iee8023/CraterDataset)), and then employed to produce a set of candidates with low omission error rate from a HRSC nadir level-4 image, that can be verified by an expert within a simple GUI, and leads to a large increase in speed when surveying a region for craters with no decrease in accuracy. This expert verification of candidates could also be used to expand the training set of the model, allowing future iterations of the algorithm to become more and more accurate.

[1] Nadine G. Barlow, Crater size-frequency distributions and a revised Martian relative chronology, In *Icarus*, Volume 75, Issue 2, 1988, Pages 285-305, ISSN 0019-1035, [https://doi.org/10.1016/0019-1035\(88\)90006-1](https://doi.org/10.1016/0019-1035(88)90006-1).

[2] G.G. Michael, G. Neukum, Planetary surface dating from crater size–frequency distribution measurements: Partial resurfacing events and statistical age uncertainty, In *Earth and Planetary Science Letters*, Volume 294, Issues 3–4, 2010, Pages 223-229, ISSN 0012-821X, <https://doi.org/10.1016/j.epsl.2009.12.041>.

[3] Roberto Bugiolacchi, Steven Bamford, Paul Tar, Neil Thacker, Ian A. Crawford, Katherine H. Joy, Peter M. Grindrod, Chris Lintott, The Moon Zoo citizen science project: Preliminary results for the Apollo 17 landing site, In *Icarus*, Volume 271, 2016, Pages 30-48, ISSN 0019-1035, <https://doi.org/10.1016/j.icarus.2016.01.021>.

[4] Breiman, L. *Machine Learning* Volume 45, Issue 1, 2001, Pages 5-32, ISSN 1573-0565. <https://doi.org/10.1023/A:1010933404324>

[5] Lourenço Bandeira, Wei Ding, Tomasz F. Stepinski, Detection of sub-kilometer craters in high resolution planetary images using shape and texture features, In *Advances in Space Research*, Volume 49, Issue 1, 2012, Pages 64-74, ISSN 0273-1177, <https://doi.org/10.1016/j.asr.2011.08.021>.

[6] J.P. Cohen et al., Crater Detection via Convolutional Neural Networks. 47th Lunar and Planetary Science Conference, 2016, <https://arxiv.org/abs/1601.00978>