CONVOLUTIONAL NEURAL NETWORKS CRATER DETECTION ALGORITHM TECHNOLOGY FOR AUTOMATED CRATER COUNTING. S. Zirnov[1], P. A. Johnson[1,2], J. C. Johnson[1,2,3], A. A. Mardon[1,2]. [1]Antarctic Institute of Canada (103, 11919-82 Str. NW, Edmonton, Alberta CANADA T5B 2W4; email: aamardon@yahoo.ca) [2]Faculty of Medicine & Dentistry, University of Alberta (email: paj1@ualberta.ca), [3]Faculty of Engineering, University of Alberta (email: jcj2@ualberta.ca)

Introduction: Impact craters can be used to estimate the relative ages of surfaces in celestial bodies, detect signatures of historical weathering events, characterize the atmosphere of the celestial body, etc. [1,2] However, counting craters are challenging and time consuming.

Crater Detection Algorithms: Automated crater counting can overcome limitations of manual counting by reducing human error, and reduce the time required. While astronomers have examined various ways to automate the process and make it more efficient, and less time consuming, one of the main challenges of automated crater counting is the detection of craters. Crater Detection Algorithms (CDAs) refer to processes of identifying and count the numbers of craters. Currently however, many CDA techniques are limited due to the spatial redundancies, and difficulties in detecting the elliptical rim due to shape erosion on crater surfaces.

Convolutional Neural Networks: There are several CDA satellite techniques, which could enable efficient to detect and automatically count the number of craters. Given current technology, techniques such as edge detection and Hough transformation, crater counting is feasible. However, these technology require the manual application of filters on the image such as Gabor or Sobel filters or Haar features [3]. Novel Convolutional Neural Network (CNN) technologies are promising and offer the machine learning capacity to dynamically learn filters. CNN systems have performed well at complex order undertakings, especially in picture acknowledgment, where pixel nearness is misused to account for scaling issues. Previous studies demonstrate CNN-based CDA can be structured utilizing Tensor Box, an open-source object location system using Google Tensor flow to produce a ground truth database [4]. Such technology can facilitate the automation of the detection and counting process. Nevertheless, there are currently no proofs that confirm the reliability of these techniques in practice. Future studies should explore the efficiency and accuracy of this method to manual counting methods. We have also determined CNNs have a greater capacity to self-learn image filters, which generate features integral for high accuracy classification.

Conclusion: CDAs are a significant area of investigation for automated crater detection and counting and characterizations of celestial bodies. CDAs can be implemented using various satellite techniques that currently exist including edge detection, Hough transformation, combined with updated CNN methods. However, there is still a need for feasibility studies to confirm the reliability of CNN methods.

References: [1] Benedix, G. K. *et al.* Deriving Surface Ages on Mars Using Automated Crater Counting. Web. Retrieved from https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019EA001005. [2] Klear, M. Data Science can count craters for astronomers - here's how (May 2018). Web. Retrieved from https://www.thinkful.com/blog/data-science-astronomy-count-craters/. [3] Johnson J.C., et al. Counting, prospecting, and analyzing craters using unmanned aerial vehicles. *Pac J Sci Technol.* In press. [4] Norman C.J., et al. Automated Detection of Craters in Martian Satellite Imagery Using Convolutional Neural Networks. *Planetary Science Informatics and Data Analytics Conference* (April 2018). LPI No. 2081.