A BIG LUNAR DATA APPLICATION: DEEP LEARNING-DRIVEN ROCKFALL DETECTION AND MAPPING WITH NASA's MOON TREK. Valentin T. Bickel[1,2], Emily S. Law[3], Brian H. Day[4], and the Solar System Treks Development Team[3] [1]Max Planck Institute for Solar System Research (bickel@mps.mpg.de) [2]ETH Zurich [3]NASA Jet Propulsion Laboratory, California Institute of Technology [4]NASA Ames Research Center

Introduction: Lunar rockfalls are interesting because they enable remote analysis of tectonic activity [1], surface evolution [2], and mechanical surface properties [3], among others. Despite the availability of more than 1.6 million high resolution images, rockfalls have not been mapped on large scales on the Moon. A Convolutional Neural Network (CNN) has been implemented and trained to automatically detect rockfalls in LRO NAC imagery. This CNN is currently being integrated as an analysis tool on NASA's Solar System Treks' (*http:s//trek.nasa.gov/*) Moon Trek webpage (*https://trek.nasa.gov/moon/*), where it can be used by the lunar community in the endeavor to utilize a large portion of available lunar Big Data and to create a global lunar rockfall map.

CNN Architecture & Performance: The used CNN (RetinaNet) was implemented in Python (Keras & TensorFlow, both open source) [4] [5]. More than 1 million augmented rockfall images have been used to train the current version of the network (4th generation). All new detections are stored and used in combination with the existing training data for periodic CNN re-training, continuously improving the performance of the neural network. The performance of the CNN has been assessed by [4], where average recall has been at ~0.7 and precision at ~0.98 for a confidence level of 0.5, with a processing time of <10 sec/image. The increase in performance across the generations is visualized in Fig 1.

Utilization & Workflow: This CNN-based tool will be accessible via Moon Trek's GUI. The user will need to select a Region of Interest (RoI) by drawing a bounding box on the lunar surface. An image selection algorithm will select the best NAC images within the RoI, based on maximal coverage, highest spatial resolution, as well as favorable illumination conditions. Next, these images and the respective meta data will be submitted to the CNN for processing. Finally, the results will be made available to the user via email, including information about rockfall locations (LAT/LON), estimated boulder diameters, NAC image resolutions and IDs, CNN confidence values, and other information.

Outlook: In order to fully automate the workflow (image selection within the RoI, data acquisition, as well as data ingestion into the CNN), a "SpaceHack Vol. 1" hackathon is to be held in May 2019 in Göttingen, Germany. The goal of this event is to involve undergrad and grad students in the production of a fully functional processing pipeline that can be directly implemented in Moon Trek.

This Deep Learning-driven, web- and cloud-based tool is able to extract valuable information from lunar Big Data. It is scalable and can be extended to automate rockfall detection on other planetary bodies in support of broader Planetary Science and Space Exploration.

References: [1] P. S. Kumar et al. (2016) *JGR: Planets* [2] Z. Xiao et al. (2013) *EPSL.* [3] V. T. Bickel et al. (2019) *JGR: Planets*, in press. [4] V. T. Bickel et al. (2018) *IEEE TGRS.* [5] Keras RetinaNet by Fizyr, URL: *https://github.com/fizyr/keras-retinanet.*

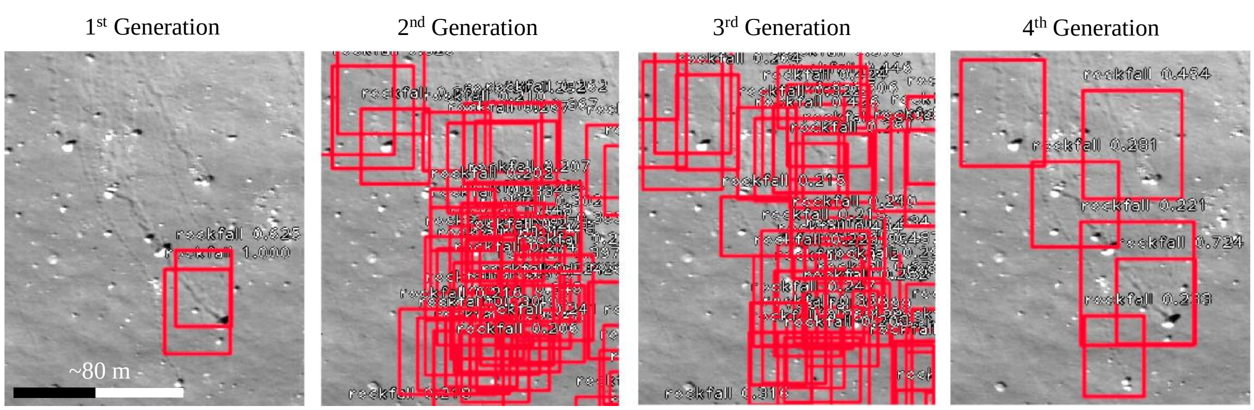

Fig. 1. CNN performance across the generations on the identical test NAC image. Rockfall detections are marked with red bounding boxes. Gen. 1 had low recall values (correct detections), which was drastically improved by Gen. 2 & 3; however, Gen.'s 2 & 3 ability to identify the concept of interest was poor, resulting in too many bounding boxes and the necessity to use NMS to post-filter the results. Due to a significantly increased training data set, Gen. 4 has a considerably improved recall and concept of interest, resulting in accurate and high-confidence rockfall detections with only minimal post-filtering needed [4].