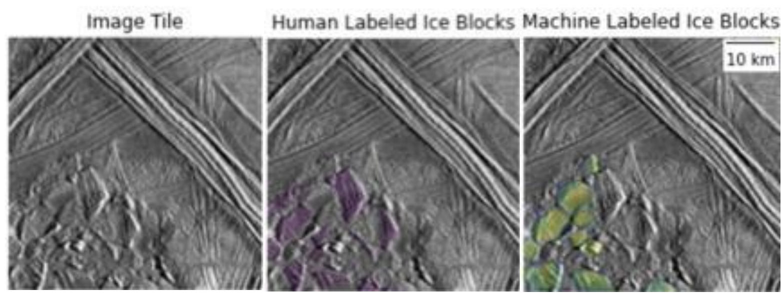
Detection and Segmentation of Ice Blocks in Europa's Chaos Regions Using Deep Learning M. M. Dunn[1,2,3], E. Duncan[1,3,4], A. C. Mills[5], J. Santerre[4], A. Larsen[6], D. M. Trent[7], I. Neidel[8], Z. Yahn[1,3,9], and C. A. Nixon[1], [1]NASA Goddard Space Flight Center (Greenbelt, MD 20771, marina.m.dunn@nasa.gov), [2]University of California, Riverside, [3]CRESST II, [4]University of California, Berkeley, [5]Baylor University, [6]Inntopia, [7]NASA Langley Research Center, [8]Yale University, [9]University of Virginia

Introduction: The young, complex surface of Europa fascinated many in planetary science and astrobiology communities for the last half-century, with intriguing observations generating speculation that underneath its icy surface, there exists a warm liquid ocean with the potential ingredients for life [1]. One extremely interesting geological feature on Europa is `chaos' terrain: areas resembling jigsaw puzzles, where broken ice blocks have separated, reoriented, and frozen again from past disruptions in the moon's subsurface [2]. It is thought the distance to the subterranean ocean may be smaller in these chaos regions, making them favorable sites for future spacecraft to land and access. Upcoming missions (e.g. ESA JUpiter Icy Moons Explorer (JUICE) [3], NASA Europa Clipper [4]) will provide additional insightful, high-quality data. Significant efforts to catalog chaos terrain on Europa by hand [5]; however, mapping locations and orientations of individual ice blocks by human eye is time-consuming and subjective. Therefore, developing methods to automate this processes going forward is crucial. In this context, we investigate using Deep Learning methods, specifically a Mask Region-based Convolutional Neural Network (Mask R-CNN) [6], to automate detection and segmentation of ice blocks in chaos regions with images from Galileo. We also explore the advantages and challenges of using the Mask R-CNN model for this particular instance segmentation task. The proposed approach aims to provide methods for accurately identifying geological features and aid in planning for future Europa and other planetary missions, and further build a framework for Machine Learning in planetary science.

Methodology: Expanding upon work by Gansler et al. (2021), which used an altered U-Net [7] framework for the same task [8], we instead explore using the computationally-efficient and straightforward Mask R-CNN model, chosen for its ability to generalize well on other image data. We initially focus on training the model on chaos regions identified by Leonard et al. (2022) as having large, "platy" ice blocks, as we expect it to generalize better on these than areas containing small and/or irregular blocks. True labels are determined by geoscientist Alyssa Mills using the procedure from Leonard et al. (2022). To evaluate model performance, we calculate the Intersection over Union (IoU) metric for images, measuring overlap between predicted and ground truth ice block bounding boxes. The most significant challenges hindering model performance are innate to input data; though Galileo imagery of Europa chaos terrain is still the best to date, it has low spatial resolution, varying solar illumination, and is relatively small for Deep Learning purposes. We attempt to overcome this by implementing a technique known as Transfer Learning and trying various optimization techniques (e.g. data augmentation).

Results: We compare model performance to that of Gansler et al. (2021), achieving a moderate improvement in IoU score from 0.286 to 0.53 (see Fig. 1) [8]. Additional methods are currently being tested to further improve this.



$$IoU = \frac{True\ Labels\ \cap Model\ Predictions}{True\ Labels\ \cup Model\ Predictions} = 0.53$$

Figure 1: Example of true and predicted labels, current best IoU score.

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