MACHINE LEARNING DETECTION OF CHAOS TERRAIN ON EUROPA AS A PROOF-OF-CONCEPT FOR USE WITH FUTURE DATA. K. R. Gansler[1], C. A. Liles[2], and , C. A. Nixon[3], [1]University of Maryland, College Park, MD. [2]NASA Langley Research Center, Hampton, VA. [3]NASA Goddard Space Flight Center, Greenbelt, MD.

Introduction: Areas of Jupiter's moon, Europa, contain irregular ice floes that are illustrative of the massive disruption, reorientation, and refreezing experienced on Europa's surface as Jupiter's gravity imparts immense tidal forces that heat the moon [1]. In recent years, various machine learning programs have been used to detect surface features on planetary bodies. Most commonly, such software works to count craters for estimating planetary surface age [2] or to map sand-filled dune fields whose shapes may indicate wind or weather patterns [3]. Creating software to automatically detect Europa's jigsaw-like ice floes will accelerate scientific analysis of such terrains once higher resolution images of the moon arrive in the fall of 2022 from the Juno spacecraft and later from the forthcoming Europa Clipper mission.

Model and Training: In this project, a U-net, a deep learning semantic segmentation model [4], was applied to images of the surface of Jupiter's moon Europa taken by the Galileo spacecraft to detect ice floes in the moon's Chaos Terrains. Designed for the segmentation of images, the original program used in this study was specifically developed to detect the outer membranes of cells in biomedical images [4]. That architecture was further altered to detect Above-Anvil Cirrus Plumes in satellite data [5]. Both studies had images where the desired features could not be isolated using basic edge detection, denoising, or arithmetic functions; this was critical, as the images of Europa had similar qualities.

Results: Hao's original U-net needed to be altered to successfully detect the ice floes on Europa. Model hyperparameters such as training rate and training epochs were tuned to improve performance. (Fig. 2).

Discussion: To measure the quality of the program developed, the Intersection over Union (IoU), a metric that measures the goodness of fit for semantic segmentation, was calculated:

$$\mathrm{IoU} = \frac{\text{area of intersection}}{\text{area of union}} \qquad (1)$$

The area of intersection is the total area of the true positives, where the training polygons outlining the ice floes overlap with the detection of floes through the algorithm. The area of union includes all areas where the either the algorithm or the human labeled a pixel as an ice floe (the sum of true positives, false positives, and false negatives) [5]. Refining the algorithm increased the IoU from its original value of 0 to 0.286. Overall, the algorithm functioned best when ice floes were hand-labeled using loose-fitting polygons rather than exact edge-mapping. Future research will seek to improve model performance through model hyperparameter tuning, data augmentation, and refinement of human labels.

As Galileo faced transmission issues, the usable dataset was limited to 23 images, 19 of which were used for training and 4 for testing. The small amount of data presented a risk of the U-net overfitting and not generalizing to new data. This was prevented by adjusting parameters like learning rate and training epochs and evaluating the model performance on the test set, even though the test set was small.

The U-net was most effective for images with resolutions near 50 meters per pixel (mpp). Currently, the average image of Europa's surface to date has a resolution closer to 500 mpp. In the coming months, data augmentation will provide additional training images that should further improve the performance of the U-net. K-fold cross-validation will also be applied across the automated dataset. This will provide a more methodical means of evaluating the effects of different hyperparameter settings during model training. Once the algorithm is sufficiently capable of identifying floes in the Chaos Terrains, it may later assist in selection of regions of interest for further study on Europa or even landing sites for a future proposed lander.

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