**DETECTION OF BOULDER BANDING ON MARTIAN LOBATE DEBRIS APRONS USING REGIONAL CONVOLUTIONAL NEURAL NETWORK ANALYSIS OF HIRISE IMAGE DATA** F. Ishraque[1] and J.S. Levy[1], [1]Colgate University Dept. of Geology, 13 Oak Drive, Hamilton NY 13346, USA. ishraque@colgate.edu

**Introduction:** Images from the High Resolution Imaging Science Experiment (HiRISE) reveal meter-scale boulders entrained in the glacial debris of remnant glacial landforms (LDA, CCF, and LDA) in the martian mid-latitudes [1]. Manual boulder distribution mapping in [2] revealed boulder clustering in these glacial deposits that was interpreted as banding that suggesting multiple episodes of ice accumulation and advance. These boulders were mapped on 100 m-wide transects down LDA centerlines, where clustering in the boulder distribution was interpreted as sections of boulder bands. However, with each centerline requiring hours to days of boulder mapping, manual detection and verification of the boulder bands is incredibly time consuming and limits the number of sites that can be evaluated. Automatic boulder detection techniques [3] have had limited success on remnant glacial landforms because of surface irregularities like "brain terrain" and serac-like ridges and furrows that can be steep enough to cast shadows which can be mis-characterized as boulder shadows [4]. Distinguishing these textures from boulders poses a difficult machine vision problem. More recently, instance segmentation methods in computer vision have excelled at predicting object class and location at a pixel-specific level in images [5].

In order to evaluate the extent to which glacier centerline boulder clusters are associated with whole-LDA bands of debris, we use an instance segmentation neural network to detect and map glacial boulders on HiRISE images of lobate debris aprons (LDA). We use the already mapped boulder data from [2] for training and testing.

**Methods:** *Generating Training Data*. Manually mapped boulder data from [2] on full-resolution (25 cm/pixel) HiRISE images was used to create training and testing data for the neural network. A total of 17 manually mapped LDA transect rasters were exported as 256 ×256 pixels image chips using a sliding window method (stride=128 pixels) along with their corresponding binary pixel masks delineating the mapped boulders in the images. Ideally, the shape of the pixel masks would have corresponded to the shape of each boulder, but since a majority of the manually mapped boulder dataset did not contain boulder widths, we chose to set circular pixel masks with diameters approximately equal to the 75th percentile of boulder diameter at each transect site. We prepared a training dataset containing 10,851 images contain 90,884 boulder masks.

*Model Training.* We used a Mask R-CNN (Regional Convolutional Neural Network), an instance segmentation neural network that can detect objects and their pixel masks in images [6]. More specifically, the Pytorch implementation of a Mask R-CNN was trained through the arcgis.learn Python module [7]. We divided the previously labeled data into two subsets: a training dataset (80% of the images) and a validation dataset (20% of the images) to be used to evaluate the model.

We trained the model for 20 training epochs (on an NVIDIA GeForce GTX 1070, with 8 GB VRAM) and used the Resnet50 backbone (which extracts a feature map from an input image) [8]. At the end of training, the model weights were saved in a model definition file.

*Detecting Boulders*. Finally, the trained model was loaded on to ArcGIS Pro to detect boulders at 5 LDA sites. Each of these sites contained a manually mapped transects down the centerline, so detection runs were performed with the Mask R-CNN over a majority of each corresponding LDA and the results were compared to the manual mapping. To evaluate significant boulder clustering in our results, we examined the spatial autocorrelation of boulders using Moran's $i$ test [9], and to estimate the number of boulder bands, we used kernel density analysis.

**Results:** *Model Accuracy.* Model accuracy of the trained Mask R-CNN was evaluated using Average Precision (AP), a method that considers true positives, false positives, and false negatives. For our trained model, the average precision was calculated to be 85% on the test (or validation) dataset, which we found was sufficient to gather representative morphometric properties of boulder bands.

*Boulder Band Detection*. Boulder bands were detected in each of the detection sites after mapping with the neural network. The observed spatial clustering was verified through significant results in Moran's i test ($i > 0.9$ and p-value $< 0.005$, indicating high positive autocorrelation). The observed boulder bands were often associated with arcuate surface discontinuities and surface lineations on LDA (Fig. 1), further suggesting the presence of internal debris layers at are advected down-glacier in response to orbitallyforced glacial/interglacial transitions [2].

Furthermore, comparing the kernel density of the RCNN-mapped boulders with the manual boulder-mapping, the boulder cluster locations align almost perfectly (Fig. 2). Note that the kernel density values in the automatic mapping is overall lower than that in the manual mapping dataset since our model is not perfectly accurate. However, since we do not expect model accuracy to vary systematically across sites, our automatic mapping provides a reliable estimate of relative spatial density of boulders.

**Conclusion:** Automatic detection of boulder banding supports the interpretation of episodic accumulation and flow model of LDA on Mars [2]. Additionally, our results are encouraging indicators of the potential of instance segmentation and other deep learning techniques in planetary geomorphology.

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**References:** [1] Golombek et al. (2012) *The Intl. Journal of Mars Science and Exploration*, 1-22 [2] Levy et al. (2021) *PNAS,* 118(4). [3] Golombek et al. (2008) *JGR*, 113 [4] Levy et al. (2010) *Icarus,* 209(2),390-404 [5] Hafiz et al. (2020) *Intl. Journal of Multimedia Info. Retr.,* 9 [6] He et al. (2017) *IEEE Computer Vision,* 2961-2969 [7] Paszke et al. (2019) *Advances in Neural Info. Proc.* Systems, 32 [8] He et al. (2016) *IEEE Computer Vision*, 770-778 [9] Upton and Fingleton (1985) *J. Wiley, Chichester, New York.*

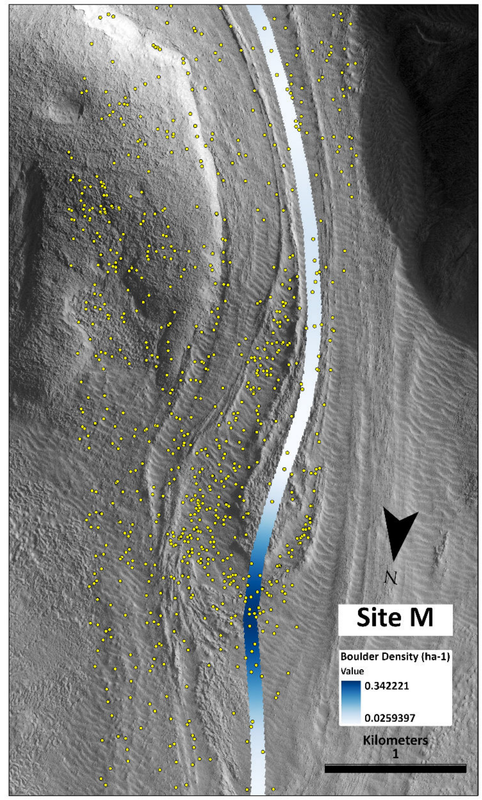


*Figure 1(above): Detected boulders (yellow points) and the kernel density (blue) from manual mapping at LDA site M (ESP_020558_2215). Notice the boulder band roughly following the surface discontinuities and aligning with the original kernel density.*

*Figure 2 (below): (Left) Kernel density along the transect from the original manual boulder mapping at LDA site L (ESP_016271_1475). (Middle) Kernel density along the same transect from the neural network mapping. (Right) Manual mapping kernel density with the boulder points mapped by the Mask R-CNN (green points). Notice that the high boulder clusters in the manually mapped kernel density align band like features in the newly mapped boulder distribution.*