Exploring CaSSIS with Machine Learning – The Search for Chloride Deposits on Mars. V. T. Bickel[1], N. Thomas[2], A. Pommerol[2], M. Read[2], A. Valantinas[2], L. Tornabene[3], V. Rangarajan[3], G. Munaretto[4], and the CaSSIS Science Team, [1]Center for Space and Habitability, University of Bern, CH (valentin.bickel@unibe.ch), [2]Space Research and Planetary Sciences, University of Bern, CH, [3]Department of Earth Sciences, University of Western Ontario, CAN, [4]Department of Physics and Astronomy, University of Padua, IT.

Introduction: Chloride deposits typically form as a result of surface water evaporation and/or volcanic outgassing [1]. Chlorides are highly soluble and readily dissolve, making them useful indicators of past aqueous activity [2]. The unambiguous identification of chloride deposits generally requires multispectral information, which is limited in spatial resolution and global coverage [1,2,3]. This implies that the current catalogs of (small-scale) chloride deposits are likely incomplete. Here, we use machine learning to systematically map chloride deposit candidates in the CaSSIS (Colour and Stereo Surface Imaging System) image dataset. CaSSIS is a 4-filter color and stereo imaging system onboard ESA's Trace Gas Orbiter [4] with a nominal spatial resolution of 4.6 m, covering ~6 % of Mars' surface as of November 2022 (33,130 images). Theoretically, CaSSIS enables the detection of very small (<< 1 km) chloride deposits.

Methods: We collate all chloride deposit instances currently known to and imaged by the CaSSIS science team (n=44). Each instance is annotated with a rectangular bounding box, referred to as labels. All labels are split into a training (n=41) and validation set (n=3) and used to tune a COCO pre-trained convolutional neural network called Yolov5x (PyTorch 1.7). In total, we train the neural net over 250 epochs (t=~10 min), while applying ample label augmentation, including rotation and radiometric modifications (brightness, hue, etc.). We further include negative training (i.e., non-chloride sites, n=62) and validation images (n=5) to reduce false positives during inference (deployment). The neural net achieves a mean average precision of 0.25 in the validation set. We note that both the training and validation set are extremely small – the validation performance is therefore unlikely to be representative of the inference performance.

We deploy the best iteration of the neural net in a pre-existing processing pipeline [5] that was modified to stream and process calibrated, map-projected CaSSIS NPB composites (NIR – near-infrared, PAN - panchromatic, BLU - blue). Chloride deposits appear in a distinct pink/violet color in NPB composites (Fig. 1). The processing of the entire NPB dataset took ~24 h (~1041 images per hour) using one NVIDIA RTX 3090, running on 4 individual threads.

Results: The neural net identified a total of 424 chloride deposit candidates with a wide range of morphologies, including continuous to intermittent deposits (Fig. 1), distributed mostly over the southern hemisphere (Fig. 2). The estimated size of the deposits ranges between ~200 meters to more than ~3 km (Fig. 3). The ratio of chloride deposit candidates/number of images scanned is 0.02.

Discussion: The map of CaSSIS-derived chloride deposit candidates is well aligned with maps generated using different datasets and (traditional) methodologies [1,2]. We note a few candidate deposit locations that were not identified by earlier work, specifically in Nepenthes Planum, Lunae Planum, and Chryse Planitia (all in the northern hemisphere). The majority of those deposits are small (<~1 km), potentially explaining why they were missed in the past. We are currently validating all chloride deposit candidates using other datasets. We note that the training/deployment of the neural net and the review of the results took less than 30 h, demonstrating the potential of machine learning-driven exploration of planetary image science datasets.

Future work: We plan to replace the bounding box-based detector with a polygon-based detector to retrieve chloride deposit shape and area. We will continue to deploy our detector(s) as CaSSIS continues to build up its image archive over the coming years.

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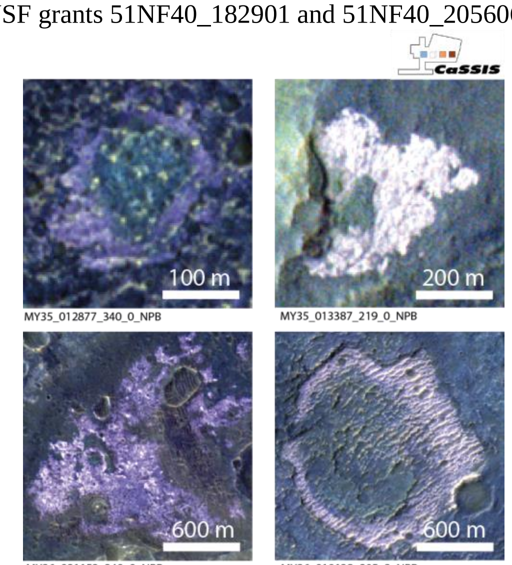

Fig. 1. Example chloride deposit candidates identified by the neural net in CaSSIS NPB images, North is up.

References: [1] Osterloo et al. (2008) Science, *319*. [2] Leask & Ehlmann (2021) AGU Advances, *3(1)*. [3] Murchie et al. (2009), JGR Planets *114*. [4] Thomas et al. (2017) Space Science Reviews, *212*. [5] Bickel et al. (2020) Nature Comms., *11*.

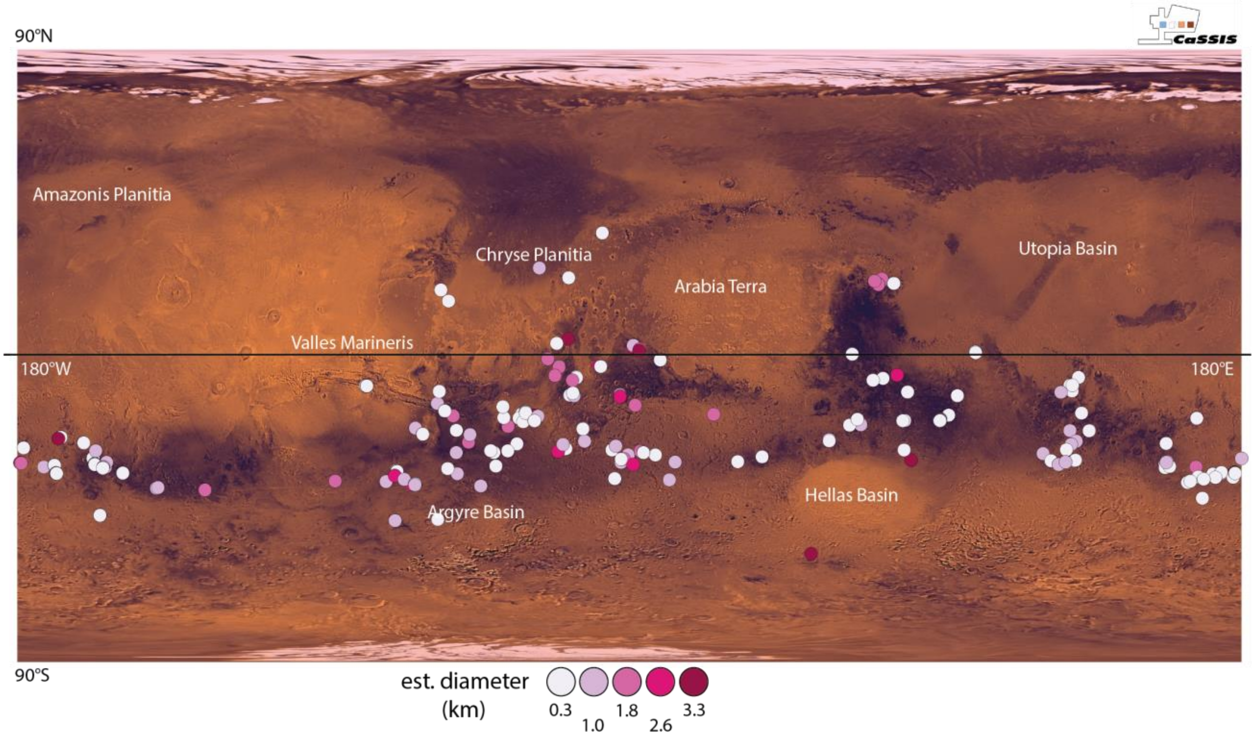

Fig. 2. Global map of neural net chloride deposit candidates. The color indicates the estimated size of each deposit. Detections are mostly constrained to the southern hemisphere and align well with maps published earlier [1,2]. The neural net identified potentially unknown deposits in Nepenthes Planum, Lunae Planum, and Chryse Planitia. Viking mosaic in the background.

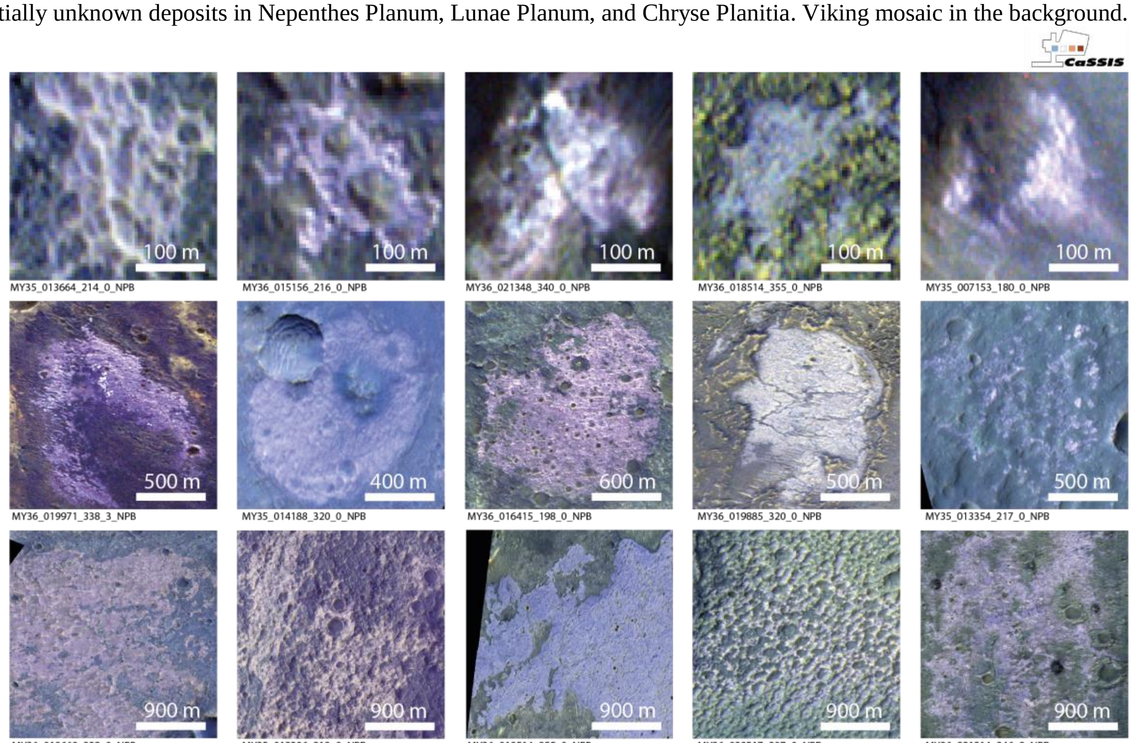

Fig. 3. Additional chloride deposit candidates (pink/violet) identified by the neural net in CaSSIS NPB composites (both hemispheres), North is up. The sizes of deposits range from small (~200 m, top row) over intermediate (~1.5 km, middle row) to large (>~3 km, bottom row). The chloride deposit morphologies range from continuous to intermittent.