# RESIST: TOOL TO AUTOMATICALLY SEGMENT MARTIAN INVERTED CHANNELS IN HIRISE IMAGES

K.P.G. Pathirana[1], C.B. Rathnayaka[1], W.G.C. Silva[1], T.D. Ambegoda[1], R. Manogaran[2], S. Karunatillake[2].
[1]Department of Computer Science and Engineering, University of Moratuwa, Moratuwa, Sri Lanka
[2]Department of Geology and Geophysics, Louisiana State University, Baton Rouge, LA.

**Introduction:** Inverted channels, forming networks of sinuous ridges, provide strong evidence for fluvial activity on early Mars. Imagery from the HiRISE gives a detailed plan view of these inverted paleochannel features formed during early conditions of Mars (Noachian to Hesperian eon) that underwent differential erosion [1][2]. However, extensive mapping to interpret underlying paleoclimates and channel-bed cementing processes has been thwarted by intensiveness and user-expertise dependence of manual image segmentation. Automating such mapping will aid ongoing investigations in areas like Aeolis Dorsa.

To distinguish inverted channels, we are developing a tool to automatically segment Martian inverted channels in HiRISE images named RESIST (Resource Efficient Satellite Imagery Segmentation) as an open-source application with a deep learning model embedded in its core. A small, labeled dataset is used to train the model. The model is expected to overcome the challenges – especially expertise dependence – of manually delineating inverted channels in HiRISE images. Since the morphology of inverted channels resembles curvilinear structures, our proposed model adapts novel techniques used for retinal vessel segmentation [3][4] and neuron boundary segmentation [5]. We also expect to minimize the erroneous results in manual annotation due to ambiguities like wrinkle ridges, eolian bedforms, and crater rims.

**Dataset and Method:** The initial dataset used to develop RESIST consists of 23 HiRISE images of the Martian terrain. The images are 2048 pixels in width and in the range of 2215-6481 pixels in height.

The dataset is annotated using the cloud-based image annotation platform Dataloop AI [6] and a mask is created per image distinguishing the inverted channels, creating two classes: inverted channel class and background class. The manual annotation process is made difficult due to the presence of ambiguities in features, drastic changes of texture among the images, the presence of shadows in the images, and the difficulty to identify the boundaries of the channels. To overcome these challenges, the annotations are reviewed geologically and refined.

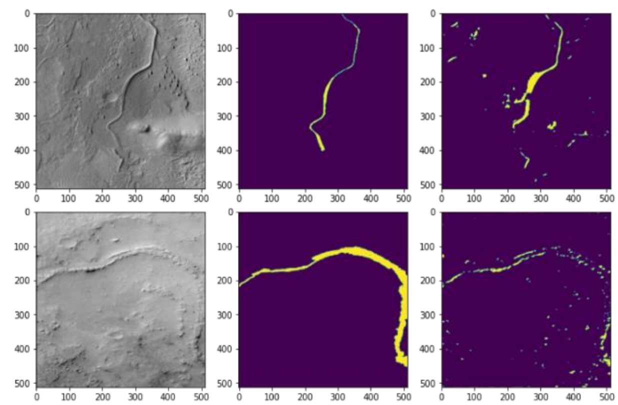


*Figure 1: 'A' shows the original HiRISE images (ESP_072116_1740, ESP_016631_1770). 'B' shows the manual annotations (Ground truths). 'C' shows the initial predictions of the model.*

**Automatic segmentation of inverted channels:** A deep learning model [3][4] is designed and implemented to segment the inverted channels in the HiRISE images. The model aims to perform automatic binary semantic segmentation [7], where the satellite images are segmented by classifying whether each pixel is part of an inverted channel or not, as shown in Fig. 1.

***Data Augmentation:*** As the dataset is small in size, multiple data augmentation methods were used to increase the dataset size. Each HiRISE image and its mask are broken into overlapping patches of size 256 x 256.

In the HiRISE images, the inverted channel class represents a significantly smaller area compared to the background class. To handle this class imbalance, horizontally and vertically flipped copies of the patches, where inverted channels occupy more

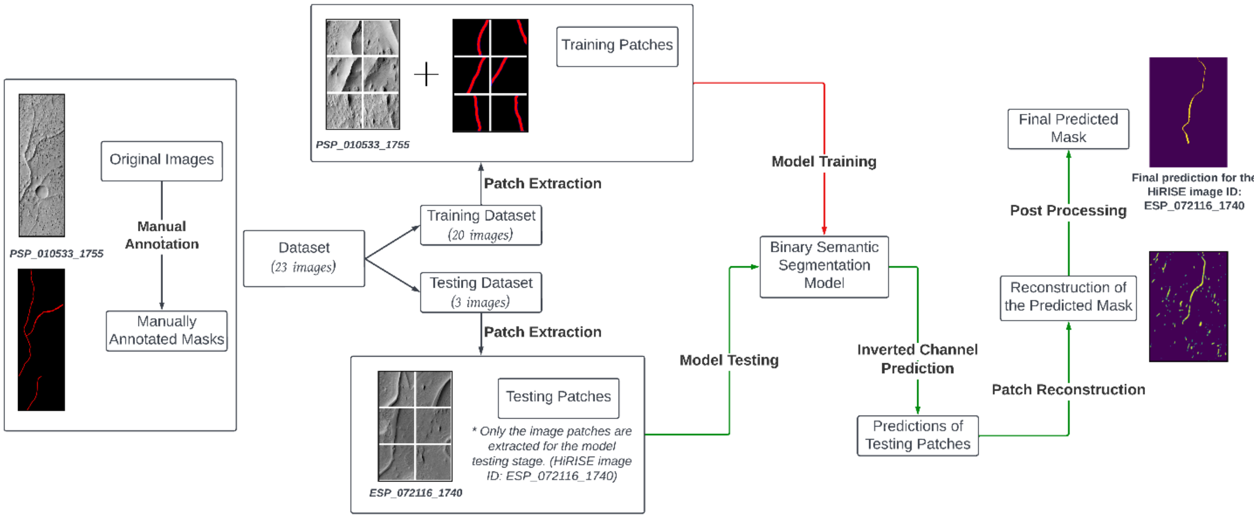


*Figure 2: Flowchart for the Martian Inverted Channel Automatic Segmentation System.*

than 10% of the total area of the patch, are added to the dataset.

***Model Implementation:*** - Fig. 2 provides a high-level view of the process followed for the implementation. The dataset is split into two:1. 20 images as the training dataset, 2. 3 images as the testing dataset. The patches generated from the training dataset are used to train a binary semantic segmentation model. The binary semantic segmentation model is implemented by combining two of the best-performing U-Net-based models for retinal vessel segmentation, Iternet [3] and SA-Unet [4]. The combined model comprises an SA-Unet as the base module and an iteration of 3 mini U-Nets as refinery modules. SA-Unet is a lightweight network where a spatial attention module is introduced to the standard U-Net [8]. The mini U-Nets are lightweight versions of standard U-net architecture and are aimed to infer missing parts in the segmentation using the well-extracted features of the base module [3]. It is trained with a modified weighted average dice loss function [9] by allocating higher weights for the inverted channel class. After training the model it is tested against the test dataset.

As the model is trained for image patches of 256 x 256 pixels in order to reduce the computational resource requirement, the testing dataset must also be split into patches with the same dimension for higher accuracy. Those patches are given as the input for the model to generate the predictions. These predictions are then stitched together to generate the whole mask in the original dimensions.

**Discussion:** Our machine learning model automatically segments inverted channels in a computationally efficient way. As this model can segment inverted channels in any HiRISE image, it can significantly help the exploration of Mars. But the ambiguities present in the satellite images cause false positives in the predicted masks for the inverted channels, lowering the precision of the model.

Our upcoming work will incorporate implementing a separate post-processing layer integrated with local constraints to remove the false positives and developing an open-source application that can identify inverted channels on a single HiRISE image or in an area of Mars marked using geo coordinates.

**References:** [1] B. D. Boatwright, et al. (2022). Planetary and Space Science. doi: 10.1016/j.pss.2022.105621 [2] A. Lefort. et al. (2012). Journal of Geophysical Research: Planets, vol. 117. doi: 10.1029/2011JE004008 [3] L. Li. et al. (2020). 2020 IEEE WACV. doi: 10.1109/WACV45572.2020.9093621 [4] C. Guo. et al. (2021). 2020 25th ICPR. doi: 10.1109/ICPR48806.2021.9413346 [5] Ambegoda TD. et al. (2020). doi: 10.48550/arXiv.2002.01036 [6] Dataloop “Dataloop ,” Online, 2021. [Online]. Available: https://dataloop.ai. [7] X. Liu. (2018). Artificial Intelligence Review. doi: 10.1007/s10462-018-9641-3 [8] O. Ronneberger, et al. (2015). Lecture Notes in Computer Science. doi: 10.48550/arXiv.1505.04597 [9] S. Jadon. (2020). IEEE CIBCB. doi: 10.1109/CIBCB48159.2020.9277638