AEOLIAN BEDFORM CREST DETECTION USING MACHINE LEARNING AND CANNY EDGE DETECTOR. E. V. Bohacek[1], A. M. Barrett[2], M. R. Balme[2], E. A. Favaro[2], E. Sefton-Nash[1] [1]European Space Agency (ESA), European European Space Research and Technology Centre (ESTEC), Netherlands (eleni.bohacek@tuta.io), [2]School of Physical Sciences, The Open University, Walton Hall, Milton Keynes, UK.

Introduction: Apart from the Earth, no planetary body is mapped more extensively and to such fine resolution as Mars. The increasing volume of remote sensing data means we are better equipped than ever to answer the fundamental questions about the history of the planet. However, the volume of data grows much faster than the number of scientists who can use it. Machine Learning (ML) is a powerful tool for automating the analysis of ever-increasing volumes of remote sensing data.

Aeolian bedforms exhibit varied morphologies at different scales in remote sensing imagery, therefore, automated detection is a complicated problem. Linear dune fields have been successfully characterized at regional scales using edge detection on Titan from synthetic aperture radar images [1]. Within the field of Earth observation, an edge detection algorithm has been proposed that is optimized for recognizing linear dune fields in panchromatic Landsat 8 data and digital elevation models [2]. Fingerprint minutiae extraction software designed for forensic applications has also successfully detected dune crests and their bifurcations and terminations for linear dunes in the Namib Sand Sea and Strzelecki Desert, and for Transverse Aeolian Ridges (TARs) on Mars [3].

A method for mapping aeolian ripples has been demonstrated using HiRISE imagery from Gale crater [4]. Similarly to earlier studies, this uses a two-step algorithm that segments the bedforms from the surrounding terrain and then detects the crestlines [5]. This study uses the same approach but with a segmentation step that classifies bedforms according to scale and morphology as opposed to foreground-background.

The aim of this study is to create a more general bedform detector that can be applied over larger and more texturally diverse areas of Mars. Moreover, it must perform as well as a geologist at mapping crestlines. This will be assessed in terms of the crest line maps produced but also in terms of the inferred wind regime. The secondary goal of this study is to demonstrate how ML terrain classifications designed for rover navigation can be repurposed for science.

Method Development: A machine learning system called the Novelty or Anomaly Hunter – HiRISE (NOAH-H) has been developed to classify terrain in HiRISE images from Oxia Planum and Mawrth Vallis according to texture. It was designed to assess terrain for rover traversability but also demonstrates great potential to be used for science [6]. Each pixel of an input HiRISE image is assigned one of 14 classes. These classes represent every type of terrain that can be found at the Oxia Planum and Mawrth Vallis landing sites, summarized in table 1. Classes 8 through to 13 are the six types of ripple morphology that are recognized by NOAH-H.

1	Non-bedrock	Smooth, Featureless
2		Smooth, Lineated
3		Textured
4	Bedrock	Smooth
5		Textured
6		Rugged
7		Fractured
8	Large Ripples	Simple form, Continuous
9		Simple form, Isolated
10		Rectilinear form
11	Small Ripples	Continuous
12		Non-continuous, Bedrock substrate
13		Non-continuous, Non-bedrock substrate
14	Other Cover	Boulder fields

Table 1: Ontological classes used by NOAH-H. Large refers to decimeter scale features and small refers to meter scale features.

The class "large simple form isolated ripples" corresponds to TARs in these regions and we use the NOAH-H output to segment the TARs from the surrounding terrain. The Canny edge detection algorithm is run on these regions in order to extract the crests of the bedforms. The steps of the algorithm are as follows [7]:

1. Apply a gaussian blur to the image
2. Find intensity gradients
3. Suppress pixels that are not part of an edge
4. Thresholding of edges according to gradient strength

Preliminary results show the algorithm can pick out portions of TAR crests but also unwanted features. The next steps are tuning the edge detection thresholds so that it works around the whole HiRISE image, potentially using an adaptive method, and suppressing the signals from features that are not TARs. After a crestline detector has been refined for the “large isolated ripples" class, the next steps are to refine the crest line detection method for the remaining five ripple classes detected by NOAH-H. The proposed pipeline for the more general bedform crestline detector is to use NOAH-H to segment the HiRISE image, and then to run each refined version of the edge detector on each bedform class.

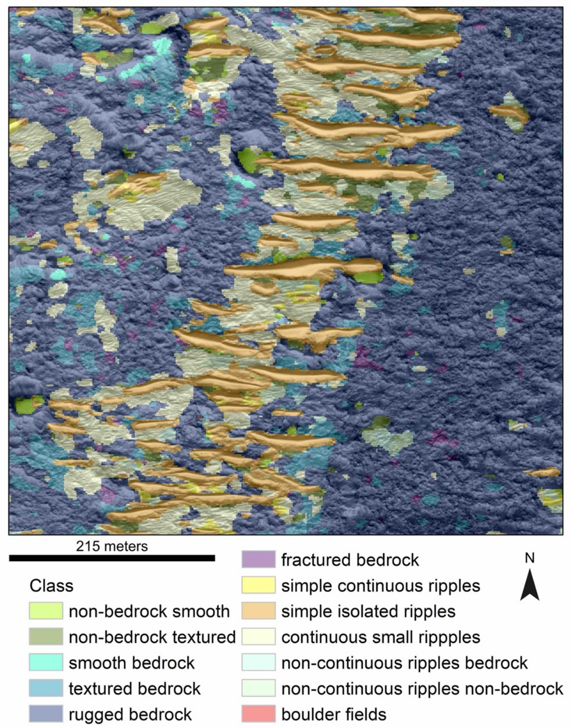

Figure 1. Translucent NOAH-H classification overlain on HiRISE image (ESP_040921_1985_RED). Large isolated ripples and small ripple fields overly predominantly rugged bedrock.

Planned Analysis: The Aeolian environment of the site of the ExoMars "Rosalind Franklin" Rover has been characterized using manual observation techniques of 10,753 aeolian bedforms [8]. To validate that the proposed pipeline picks out bedform crests as well as a geologist, the results will be compared with the bedform crests mapped in the Favaro et al. study. The bedform crests will be exported as shapefiles and compared using GIS software. They will also be compared in terms of mean crestline orientation within 4x4 km framelets. They will also be compared in terms of inferred wind regime and compared with a global climate model to see if they give the same conclusions.

References: [1] Lucas A. et al. (2014) *JGR*, 41, 6093–6100. [2] Telfer M. W. et al. (2015) *Aeolian Research*, 19, 215-224. [3] Scuderi L. (2019) *Aeolian Research*, 39, 1-12. [4] Vaz D. A. and Silvestro S. (2014) *Icarus*, 230, 151-161. [5] Pina P. et al. (2004) LPS XXXV, Abstract #1621. [6] Barrett A. M. et al. (2022) *Icarus*, 371, 114701. [7] Canny J. (1986) *IEEE TPAMI*, PAMI-8, 6, 679-698. [8] Favaro E. A. et al. (2021) *JGR Planets*, 126, e2020JE006723.