Automated Mineral Mapping On Mars Using a Generative Adversarial Network

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Background

- Mars' minerals and rock types offer crucial insights into its past climate and environment, especially aqueous minerals which hint at the geochemistry of ancient Martian waters [1]
- The Compact Reconnaissance Imaging Spectrometer (CRISM) revolutionized mineral identification on Mars by acquiring high-resolution spectral images of the surface
- Previous methods do not fully automate the mapping process and are not objective [2]
- Building on Saranathan and Parente (2021)'s [3] use of a Generative Adversarial Network for automatic mineral mapping from CRISM images
- **Aims:**
  - Create an automatic pipeline for mineral maps
  - Broaden the number of minerals that can be identified
  - Improve the accuracy of mineral selection thresholds using a Receiver Operating Characteristic
  - To map an area of Mars that contained ancient water to see how this has affected the minerals

Generative Adversarial Network (GAN)

- Unsupervised machine learning method that utilises two convolutional networks
- The two networks compete in an adversarial game, this improves their ability to learn patterns in the data [4]

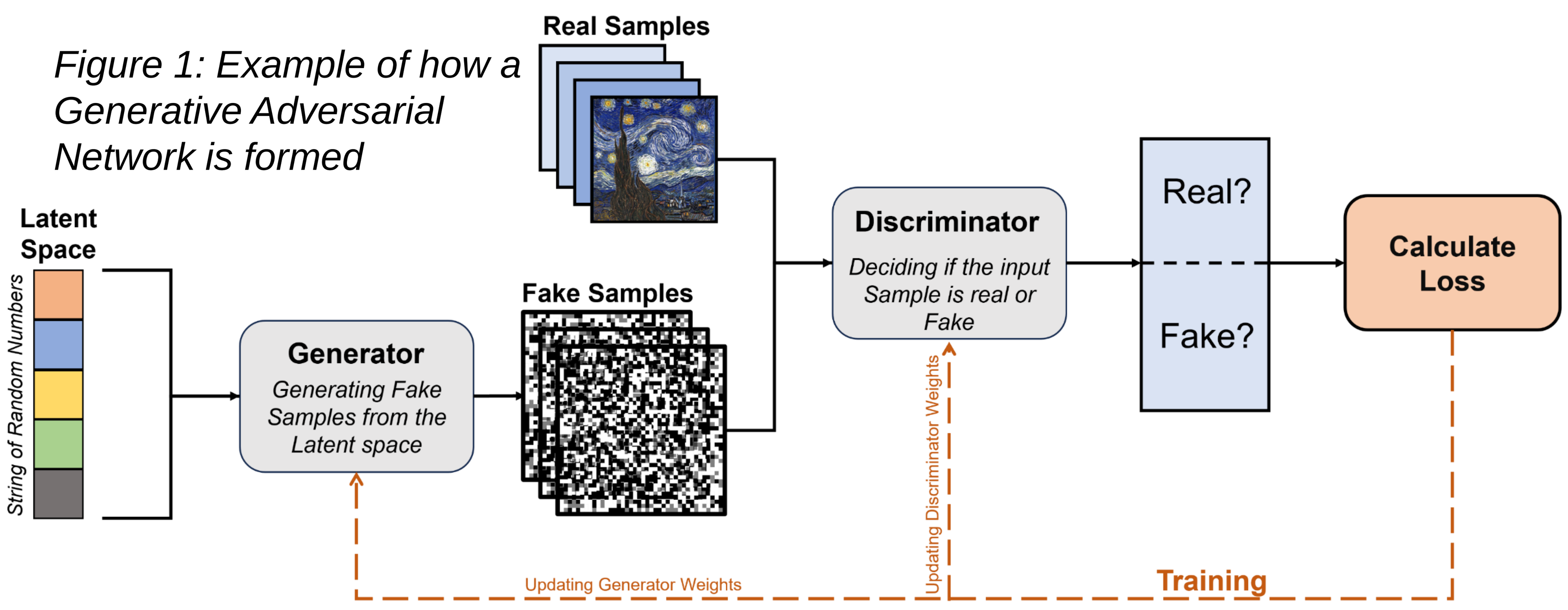


Figure 1: Example of how a Generative Adversarial Network is formed

- Need to build a strong generator to create more training data

Methods

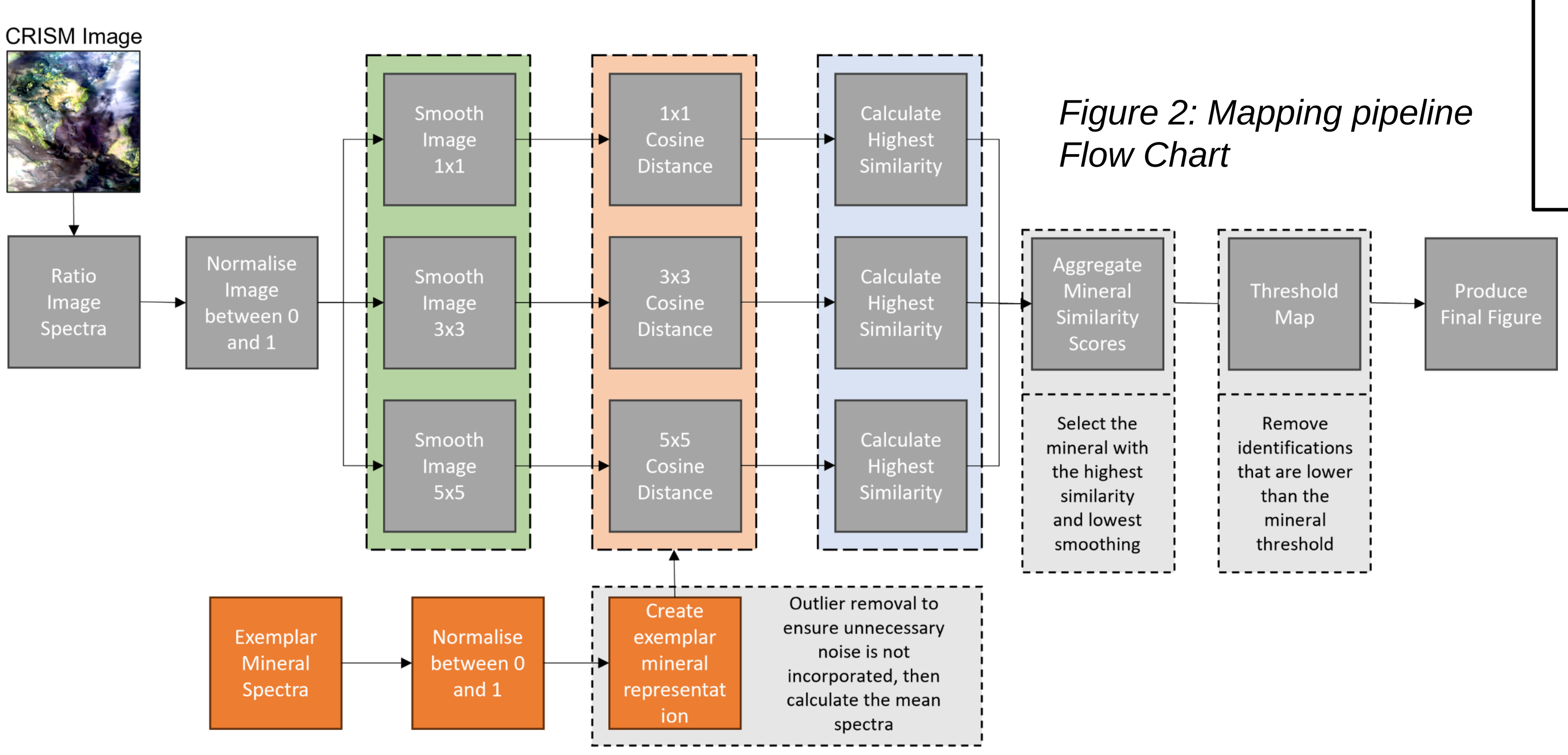


Figure 2: Mapping pipeline Flow Chart

1. GAN is trained until it has learnt the patterns within the spectral data
2. CRISM image is selected and smoothed at different levels
3. Similarity score is calculated between each pixel in the image and each labelled mineral
4. The mineral with the highest similarity for each pixel is selected
5. If the similarity score is over a threshold; calculated using a Receiver Operating Characteristic it is added to the mineral map

Example Spectra from CRISM

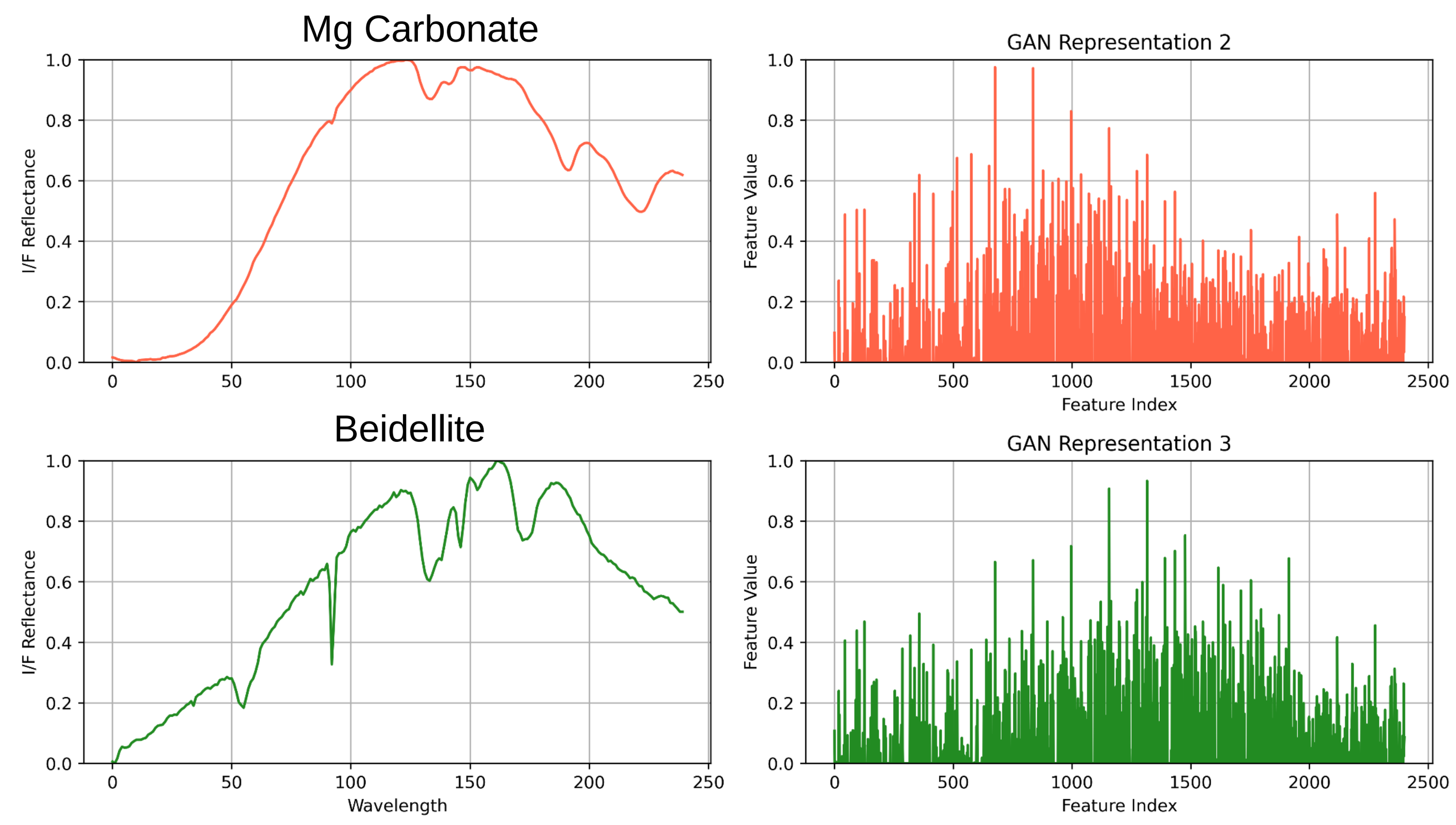
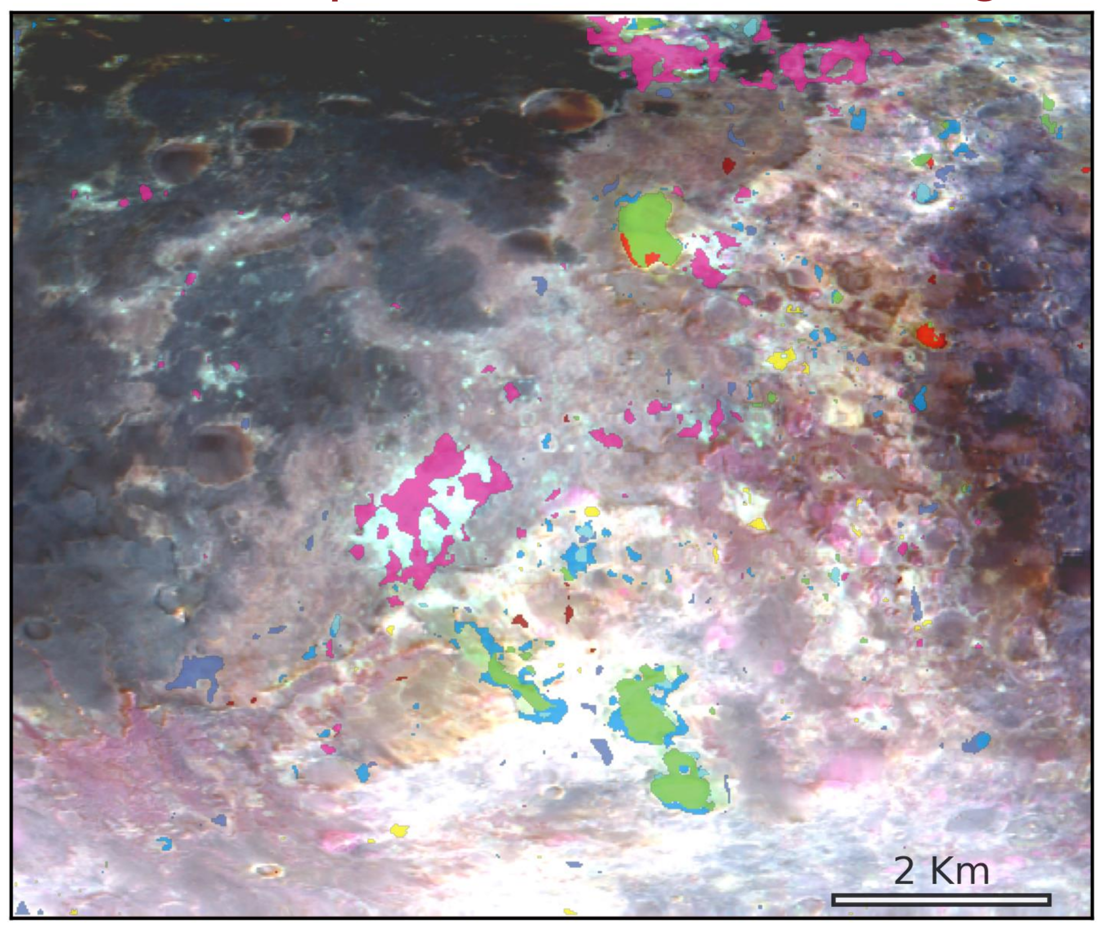


Figure 3: Example of Mineral Spectra from CRISM

Results

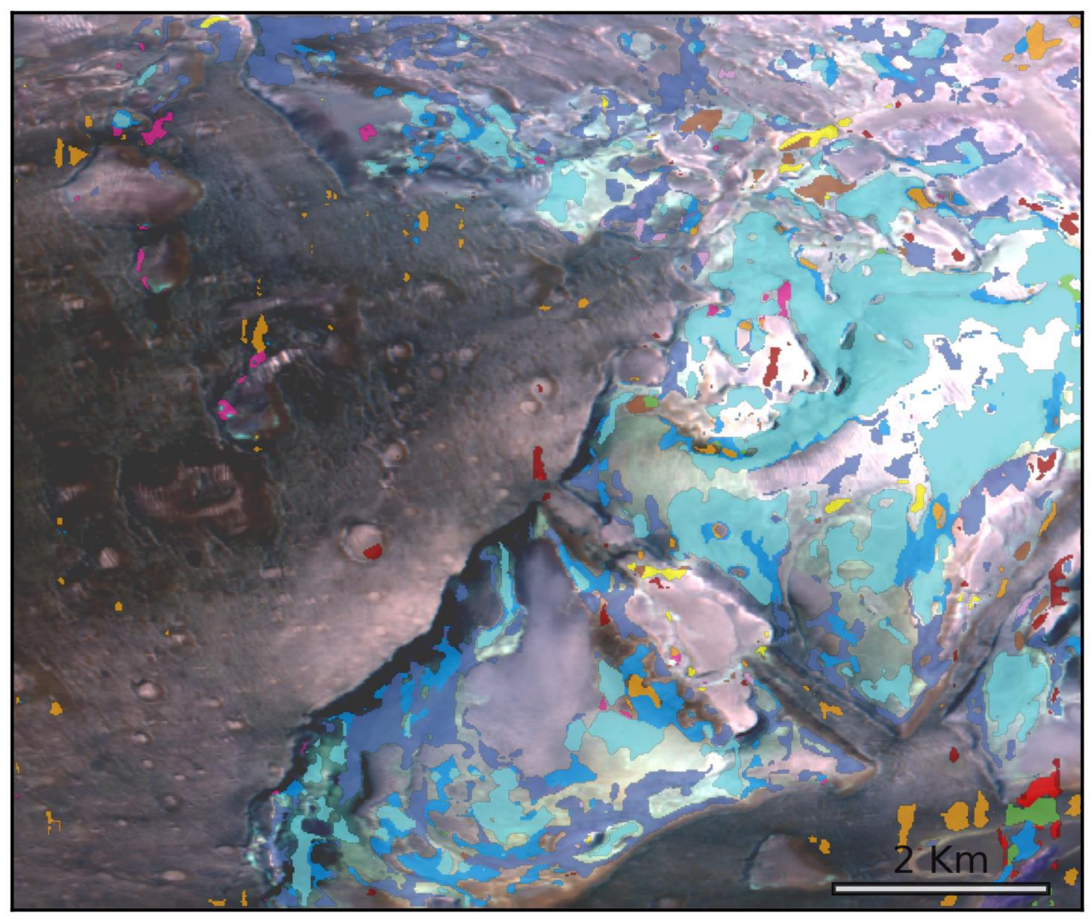
Mineral Maps of the Nili Fossae region



Mineral Colours

- Al Smectite
- Mg Smectite
- Jarosite
- Serpentine
- Kaolinite
- Mg Carbonate
- Olivine Forsterite
- Olivine Fayalite

Figure 4: Map of a crater within the Nili Fossae Region



Mineral Colours

- Fe Smectite
- Mg Smectite
- Prehnite
- Jarosite
- Serpentine
- Kaolinite
- Montmorillonite
- Mg Carbonate
- Clinochlore
- Olivine Forsterite
- High Ca Pyroxene
- Olivine Fayalite

Figure 5: Map of a crater within the Nili Fossae Region

Conclusion

- 27 minerals can be identified through the mapping pipeline
- Ratio methods produced spectra that were significantly free from noise and highlighted key absorption features
- The GAN pipeline automates mineral mapping with many successful identifications, over different regions of Mars
- Mapping results showed hydrated clay minerals within the same crater. This infers the process of Serpentinization and Carbonation of Olivine rocks

References

[1] Dundar, M. and Ehlmann, B. L. (2016), Rare jarosite detection in crism imagery by nonparametric Bayesian clustering, in '2016 8th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS)', pp. 1–5. ISSN: 2158-6276 [2] Carter, J., Riu, L., Poulet, F., Bibring, J.-P., Langevin, Y. and Gondet, B. (2023), 'A Mars orbital catalog of aqueous alteration signatures (MOCAAS)', Icarus 389, 115164.[3] Saranathan, A. M. and Parente, M. (2021), 'Adversarial feature learning for improved mineral mapping of CRISM data', Icarus 355, 114107. [4] Weng, L. (2019), 'From GAN to WGAN'. arXiv:1904.08994