AI BASED DETECTION OF LUNAR SINUOUS RILLES AND COMPARISION WITH MANUAL DETECTION METHODS

Dyutideepta Banerjee[1], Sebastian Gross[2], Franziska Albers[2], Urs Mall[3], Matteo Massironi[1], Riccardo Pozzobon[1]

[1]University of Padua, Padua, Italy , [2]MathWorks, Munich, Germany
[3]Max Planck Institute for Solar System Research, Gottingen, Germany.

1. Introduction

Lunar sinuous rilles are thought to be lava channels or collapsed lava tubes formed during mare volcanism [1]. A global distribution map cataloguing the rilles will help us in understanding the type of volcanism and lava flow viscosity, as well as detect potential lava tube entries and decide the safer landing spots for future moon missions[2]. In this progressing project, using the SELENE KAGUYA multiband images [3] and the survey conducted in 2013 that catalogued nearly 200 sinuous rilles on the Moon's surface [5] as our reference, we attempt to mark the sinuous rilles and use visualization techniques on Matlab to analyse how well our deep-learning networks [4] work on the image data. Our sample of data includes rilles from Procellarum, Imbrium, Orientale, Serenitatis, Tranquillitatis, Nubium, Sinus Aestuum and Thomson rille basins [6].

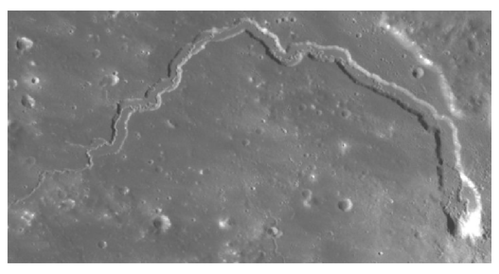


Fig. 1: Schroter's Valley from the ODE (Resolution: 0.0148 Km/ Pixels)

2. Deep-Learning Methods

- **Network architectures without pre-trained learnable parameters:** The networks train and learn from our training data from scratch. We adapt the network architectures by altering them to our needs.
- **Network architectures with pre-trained learnable parameters to perform Transfer Learning on RGB type image data**
- **10-channels multi-band image data**: The 10 channels include 1 altitude data, 5 visible spectra, and 4 near-infrared wavelength channels.
- **3-channels image data**: Mimicking a regular RGB image data type to perform transfer learning.

3. Data Creation

We prepare our gold-standard training image data (further referred to as "patches") using an application designed using GUI in MATLAB by manually marking the sinuous rilles on the raw image data with 10 channels. To visualize, we select the first DTM channel and a visible spectrum channel while marking the feature manually.

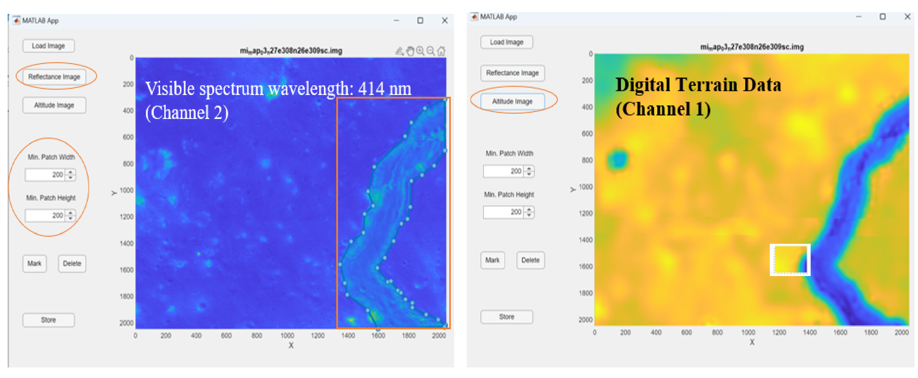
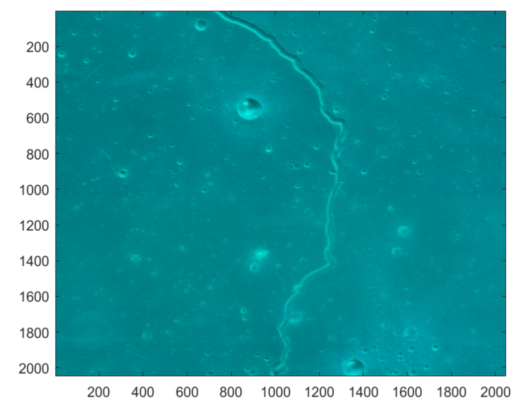


Fig. 2: We divide the images into predefined sizes (here, 200x200 pixels) with 10 channels each, and finally, save them under label names "sinuous rille" and "no sinuous rille". A cross-sectional area displays how the patch of 200x200 pixels looks on the original image.

4. 3-Channel Selection

We make an informed selection of 3 Channels from the 10-channel multi-band image data.



- **Channel 1:** DTM Data (Altitude information)
- **Channel 2:** Visible spectrum baseband of 1001 nm.
- **Channel 3:** Near-infrared of 1500 nm.

We then test for transfer learning predictions typically on how regular RGB pre-trained networks are based.

5. Prediction results on test data

Multi-band images: Prediction accuracies for different patch sizes across all non-transfer learned network architectures.

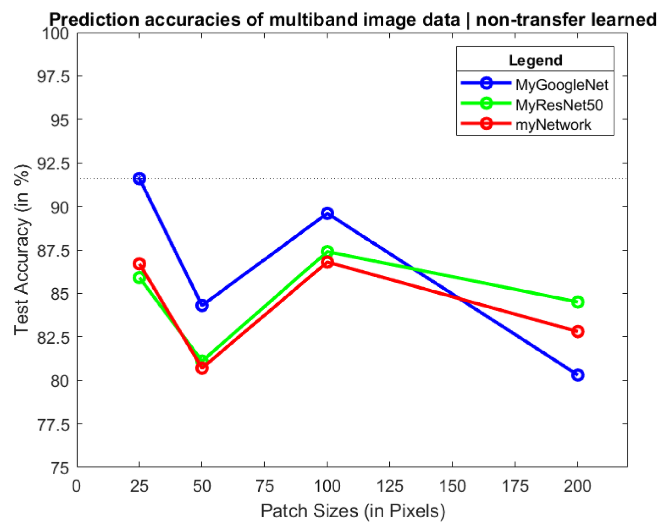


Fig. 3: The smaller the patch sizes, the higher the prediction accuracy.

Evaluating which network best classifies our prediction target class features with "sinuous rille".

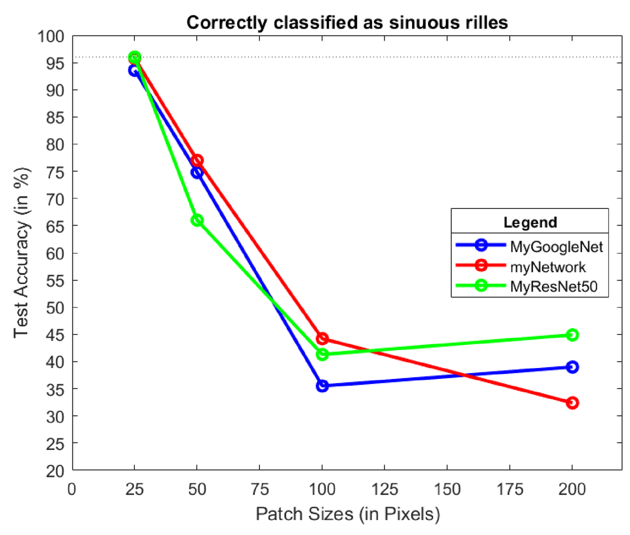


Fig. 4: The highest percentage of correct classification is given by the network resnet50

3-Channel images of patch size 200x200 pixels: Test results of the non-transfer learned method against the transfer learned method.

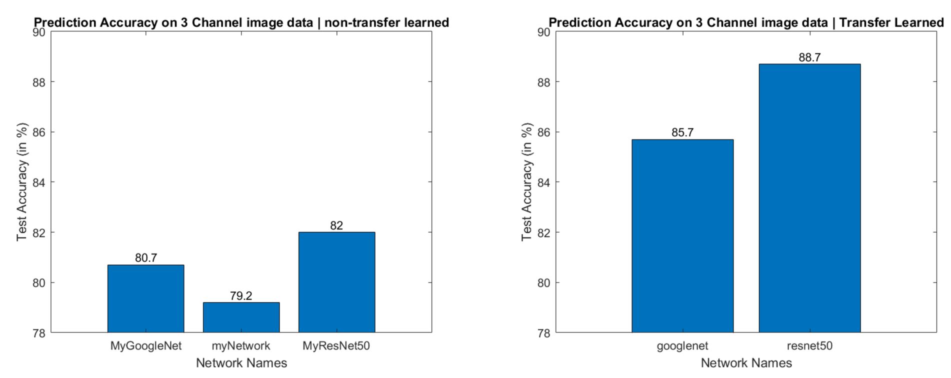


Fig. 5: renet50 predicts highest percentage of images with "sinuous rilles" correctly

6. How networks view the data

We use the GradCam analysis tool to get an idea of what parts of the image each network focuses on while performing classification analysis.

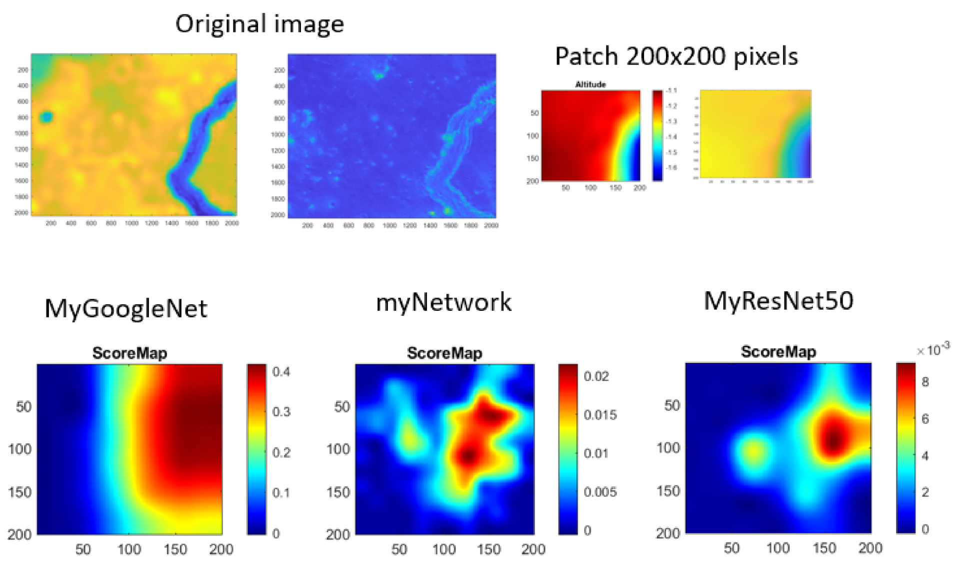


Fig. 6: Comparision of each network's visualization

- **MyGoogleNet:** Boundary & gradient.
- **myNetwork:** Boundary.
- **MyResNet50:** Meandering effect.

7. In Progress: Outlook & Conclusion

We evaluate our trained networks on a new set of feature images collected, to understand how well these architectures will perform in the future.

Testing multi-band image data across all non-transfer learned networks.

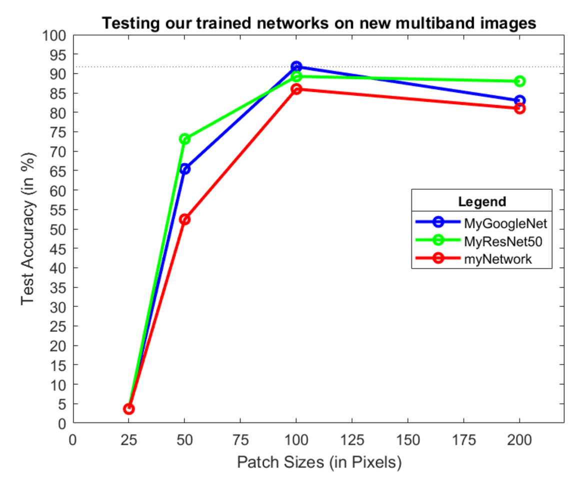


Fig. 7: Higher accuracy achieved on Patch size 100x100 pixels

Testing on 3-Channel image data on all non-transfer and transfer learned networks.

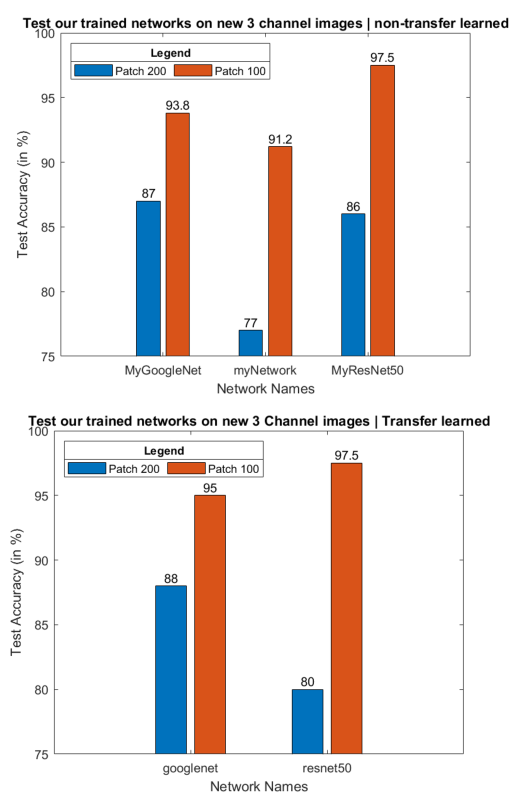


Fig. 8: Highest prediction accuracies achieved by resnet50

- Network architecture resnet50, seemingly classifying using the meandering feature (biggest distinguishing factor from other lava tubes & channels), produces the highest prediction accuracy.
- The ideal patch size for training as per our results is 100x100 pixels, area on the Moon being 1.84x1.84 Km^2.

Refrences

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Contact information:
Name: Dyutideepta Banerjee
Mail: dyutideepta.banerjee@studenti.unipd.it
Department of Physics and Astronomy "Galileo Galilei" University of Padova