

# Segmentation Convolutional Neural Networks for Automatic Crater Detection on Mars

Replication of results from original paper by Danielle M. DeLatté, Sarah T. Crites, Nicholas Guttenberg, Elizabeth J. Tasker, and Takehisa Yairi,

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*Abstract*— The selection of detector landing sites and the calculation of the Moon's age depend on the identification and tally of lunar impact craters. However, traditional crater detection methods are based on machine learning and image processing technologies. These are ineffective with different distributions and crater sizes, and most of them mainly focus on the accuracy of detection and ignore the efficiency.

## I. INTRODUCTION

One significant feature of the lunar surface is the presence of impact craters. The evolution of the moon can be inferred significantly from impact craters. For instance, craters distribution and abundance are frequently employed to calculate the Moon's age in relation to Earth, and they also serve as crucial landmarks for precise spaceship landing guidance. The identification of the permanently darkened lunar polar regions, for instance, can be done by manually analyzing and comparing photographs of impact craters with various properties. This is made possible by the discovery of impact craters on the lunar surface.

In order to detect and identify craters in digital images, we use remote sensing and supervised algorithms.

## II. RELATED WORKS

### A. Automated crater detection

Automated crater detection is a technique used to find craters from digital images taken from space and is one of the most important aspects of astronomy. When an astronaut takes a photo from space, it is usually a panoramic image of the surrounding area. However, finding individual craters from this image can be very difficult and time-consuming. This is where automated crater detection comes into play. This technique allows astronomers to quickly and easily find craters from digital images taken from space. Automated

crater detection can be done with either a computer program or a specialized machine known as a “crater finder”.

### B. Examples of automated crater detection in astronomy

One of the most prominent examples of automated crater detection is from the moon. Astronomers have been using automated crater detection to find craters on the moon since the beginning of space travel. They also use automated crater detection to find craters on other planets as well. The first image taken from space that was analyzed with automated crater detection was of the moon. Since then, automated crater detection has been used on other images taken from space to analyse the terrain of planets and moons. For example, automated crater detection has been used to analyse the surface of Mercury, Venus, and Mars. Mercury is one of the closest planets to the sun and is often used as a reference point for other planets. Since the terrain of Mercury is extremely similar to other planets, it can be used as a reference for automated crater detection.

## III. METHODS

### A. Data

In order to train a neural network in the art of deep-learning or supervised learning, a dataset of annotated data-target pairs is needed. The largest, most complete dataset of Martian craters available is that of Robbins & Hynek (RH2012) [3] [4].

We added some preprocessing steps (see training segment) that help the data.

### B. Training

The important step is visualization of data. In fact, these visualizations enable us to understand and interpret on the information represented on images.

Then, we choose one target among the 4 targets and real tiles images of mars. Before we train our model, we need to

choose an appropriate dataset preprocessing to make a difference in our model's performance.

So, we used these steps:

- ✓ Make a function which read images and convert it to matrix.
- ✓ Make a function which makes values of target binary then changes values from [0,1] to [-1,1] and then convert to numpy array.
- ✓ Split dataset into train and test data.
- ✓ Create a U-net model based on CNN with one feature (as real image) and four different masks targets and we train it with Python, TensorFlow, and Keras to determine the class that each test image belongs to.
- ✓ Choice accuracy and loss function for training and validation data and the loss function used will be adams optimizer and categorical cross entropy
- ✓ Fit the model, which will train the model by splitting the data into "batches" of size.

Finally, we make histogram and error analysis of model to show loss and accuracy result.

### C. Data Management and 3D Visualization

The first important step, is to transform data files .vtk into vector and files.mat into a dictionary of array. extract arrays from matrix files which reflect the rays of the earth, moon mars (true\_G) to show the difference in gravity constant then we apply rotation...

With the library pyvista, we use plot to show true\_G and rotation scatters by adding a white sphere inside and then transform it into 3D images.

With the libraries numpy, pyvista, scipy.io, we extract the dimension of the inner layers of the moon and mars (using internet and arrays) and display them in 3D by making a section (display half sphere and 1/8 of sphere) and then transform into half sphere and cheese form for moon and mars.

With the libraries PIL, pillow, numpy, vtk, vtk.util, we extract a 2D image ( output of the first step of the challenge) and render it as a texture , then we convert it to numpy then convert it to .vtk and as a result we display them in 3D as a planet.

## IV. TECHNOLOGIES

### A. Deep learning

It's a branch of machine learning that uses algorithm analysis to automatically learn and enhance functionality. The algorithms imitate how people think and learn by using artificial neural networks to learn and enhance their performance.

In fact, deep learning not only plays an important role in statistics and predictive modeling but also it makes it faster and easier to interpret large amounts of data and form them into meaningful information.

### B. CNN

Convolutional Neural Network (CNN) is a deep learning method used to analyze and map visual imagery, which is widely used for image recognition and classification.

### C. U-net

The convolutional neural network was created for the segmentation of biological images. The network's architecture was extended and changed from a fully convolutional network's original design in order to operate with less training photos and produce more accurate segmentation.

## V. IMPLEMENTATION

### A. First run

We run a first model using the RMSprop optimizer. It gave us the following results:

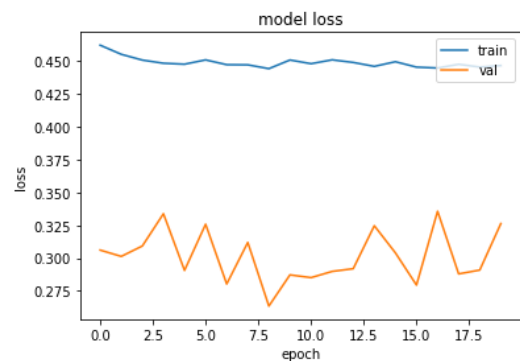


Figure 1: Accuracy plot for the first model

### B. Best Run

We tried multiple models, optimizing hyperparameters and trying different optimizers. Our best model gave the following results:

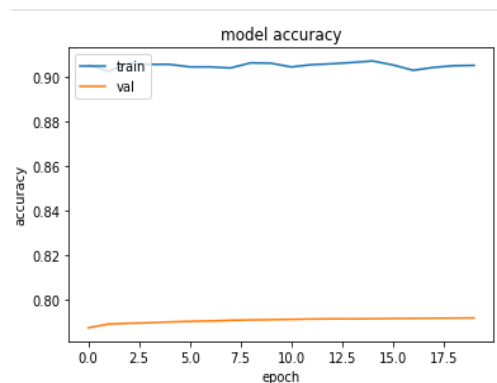
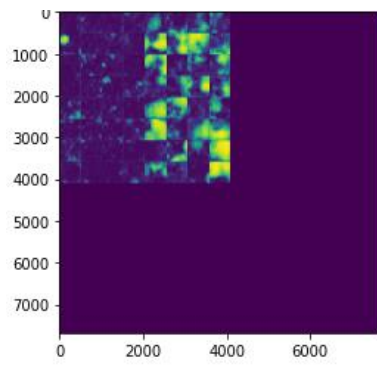


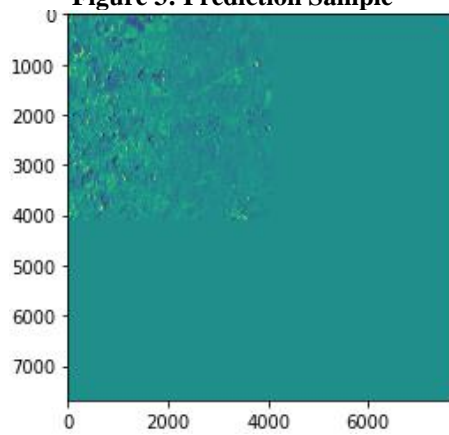
Figure 2: Accuracy plot for the best model

### C. Results

Our best model can generate the following result:



**Figure 3: Prediction Sample**



**Figure 4: Original Image**

## References

- [1] ddelatte. (2022, December 12). *CraterSegCNN*. GitHub. <https://github.com/ddelatte/CraterSegCNN>
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- [3] DeLatte, D. (2019, February 3). *Mars Crater Segmentation Dataset*. IEEE DataPort. <https://ieee-dataport.org/open-access/mars-crater-segmentation-dataset>