Automatic crater detection and classification using Faster R-CNN

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Introduction

Counting craters is a way to make relative datation of planetary surfaces [1]. Indeed, surface age is correlated with the crater density [2].
Manually counted crater database exist [3,4] but they are imprecise and not exhaustive especially for small crater size, since the method used is error-prone and time-consuming [5]. There is a need of automatising the detection task.
An exhaustive crater database might give us a better comprehension of planet formation and evolution.

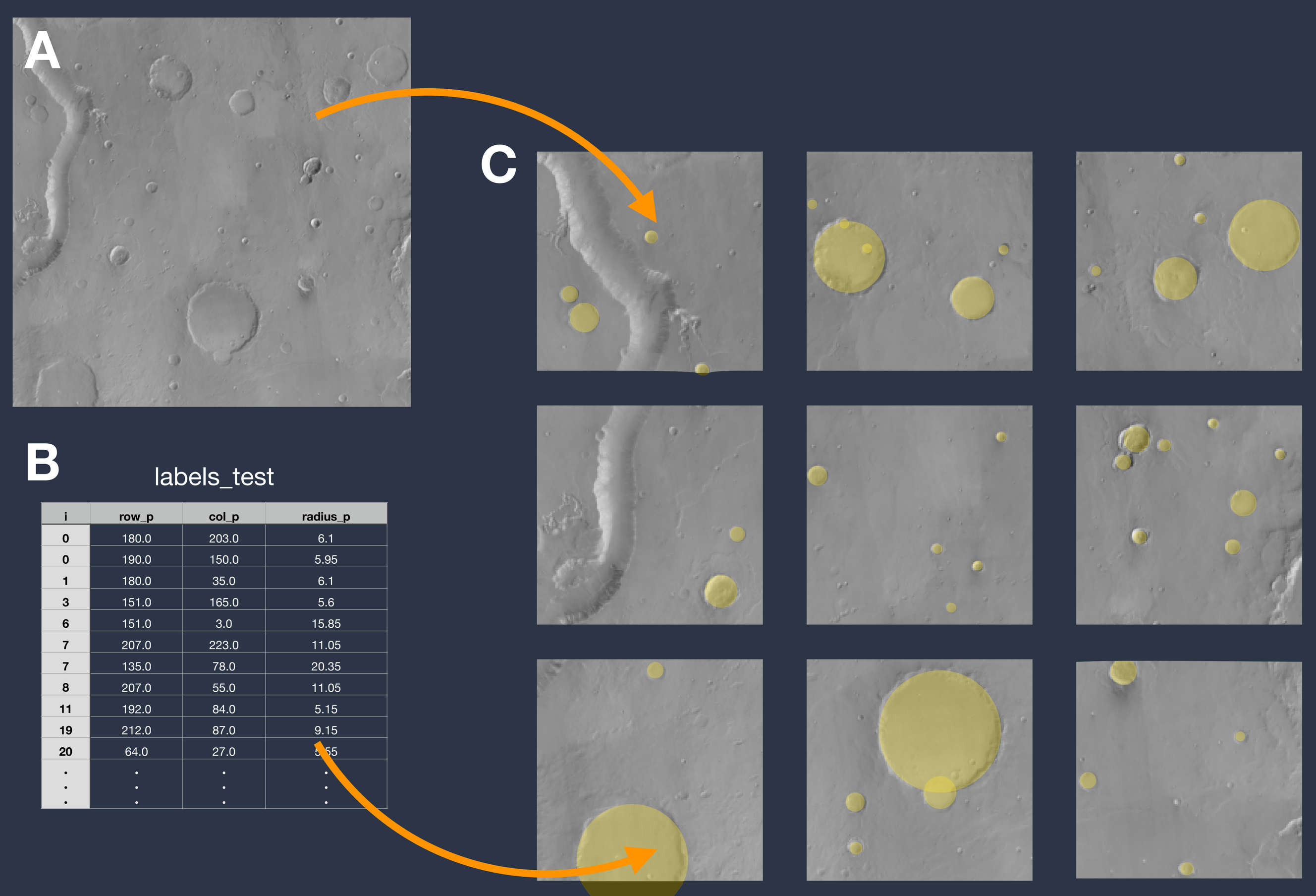

Fig 1. Illustration of the two dataset that we use to train our model.
***A** : CTX images ; **B** : Lagain & al., 2021 [6] crater database*
***C** : Illustration of the preprocessing step (re-projection and crop)*

Data

To train our model we have two different dataset :

- Mars Reconnaissance Orbiter Context Camera is a database providing high resolution imaging of the surface of Mars.
- Lagain et al., 2021 [6] is a handmade crater database made by 56 planetary scientists

First, we cut the whole CTX mosaic into 3960 4°x4° quadrangles. Afterward, we re-project our image from an equidistant cylindrical to a local stereoscopic projection. Then, we cut the CTX mosaic to create 224x224 pixels labelised images.

Method

To tackle this issue, we used a Convolutional Neural Network called **FasterRCNN**, which is a powerful object detection algorithm.
It was train several times on the whole train dataset (82 874 images) and evaluated on another dataset (4 828 images). Then, it will be ready to detect craters on any images.
The training time was approximately 60h on a Nvidia GTX TitanX 12Gb GPU.

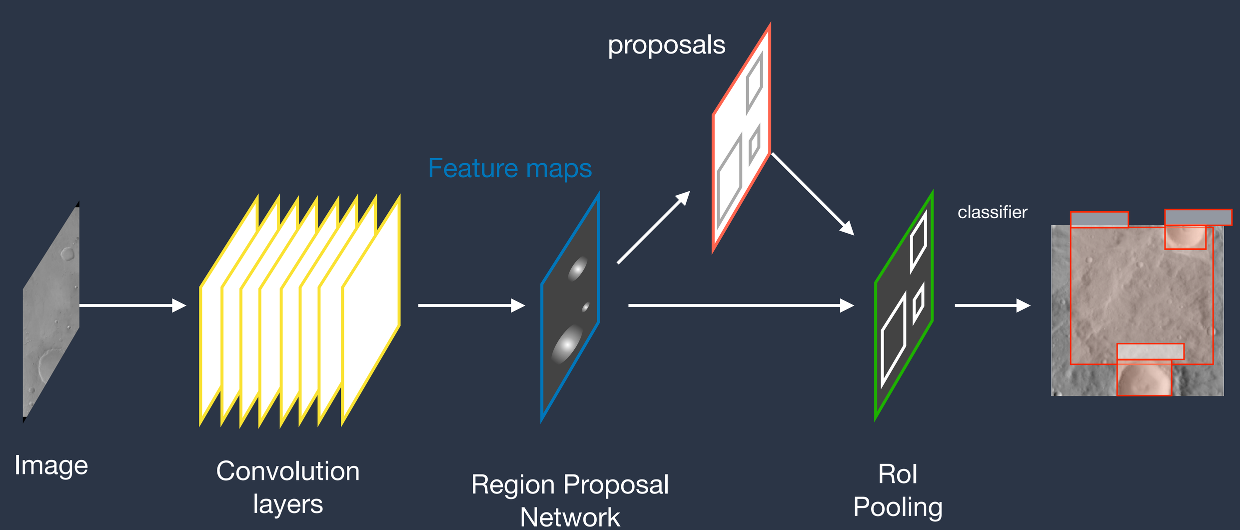

*Fig 2. Schematic view of our **FasterRCNN** detection model. It takes images as entry and gave detection, labels and confidence score as output.*

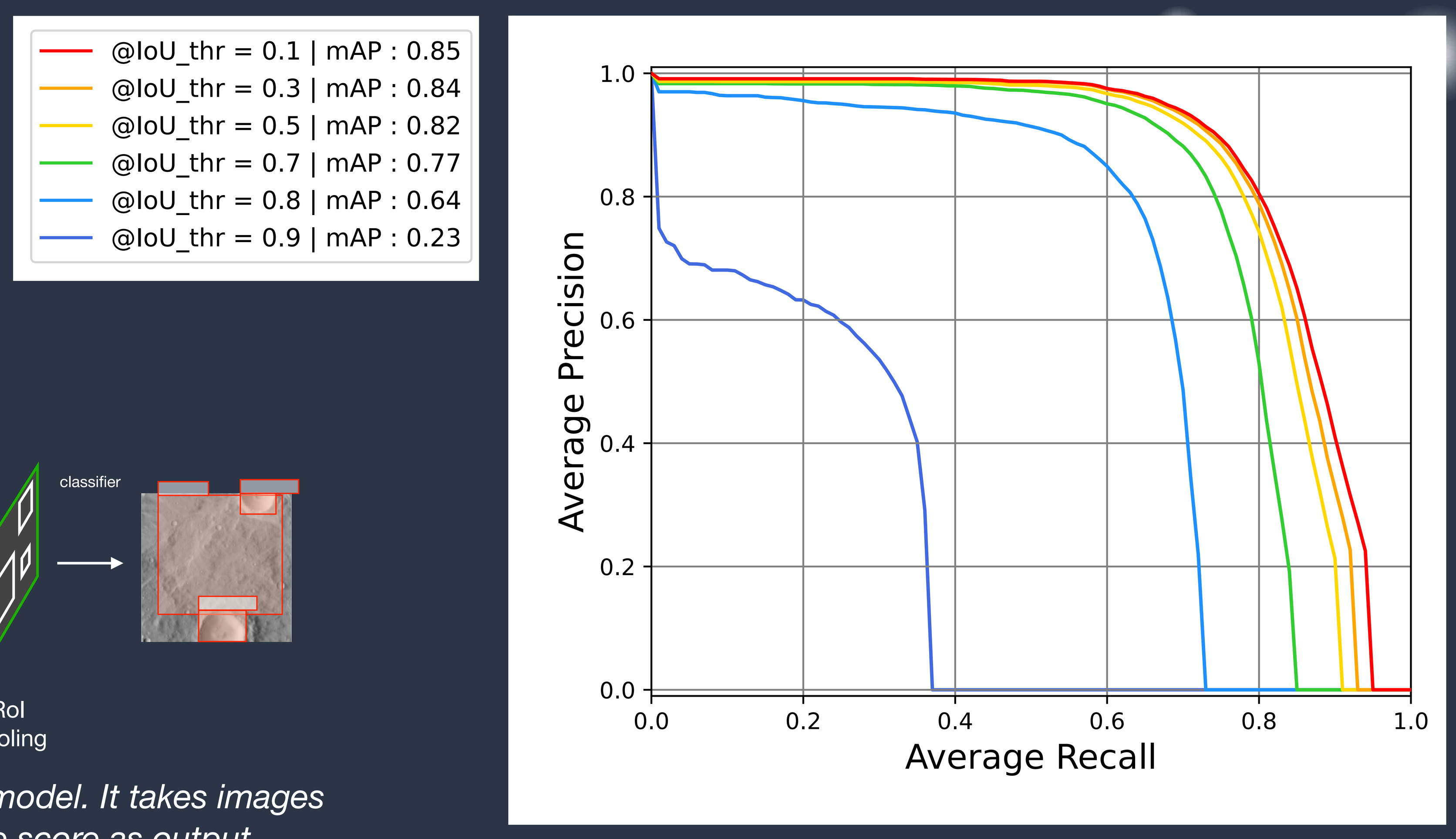

Fig 3. Performance curves of our detection algorithm for different IoU thresholds.

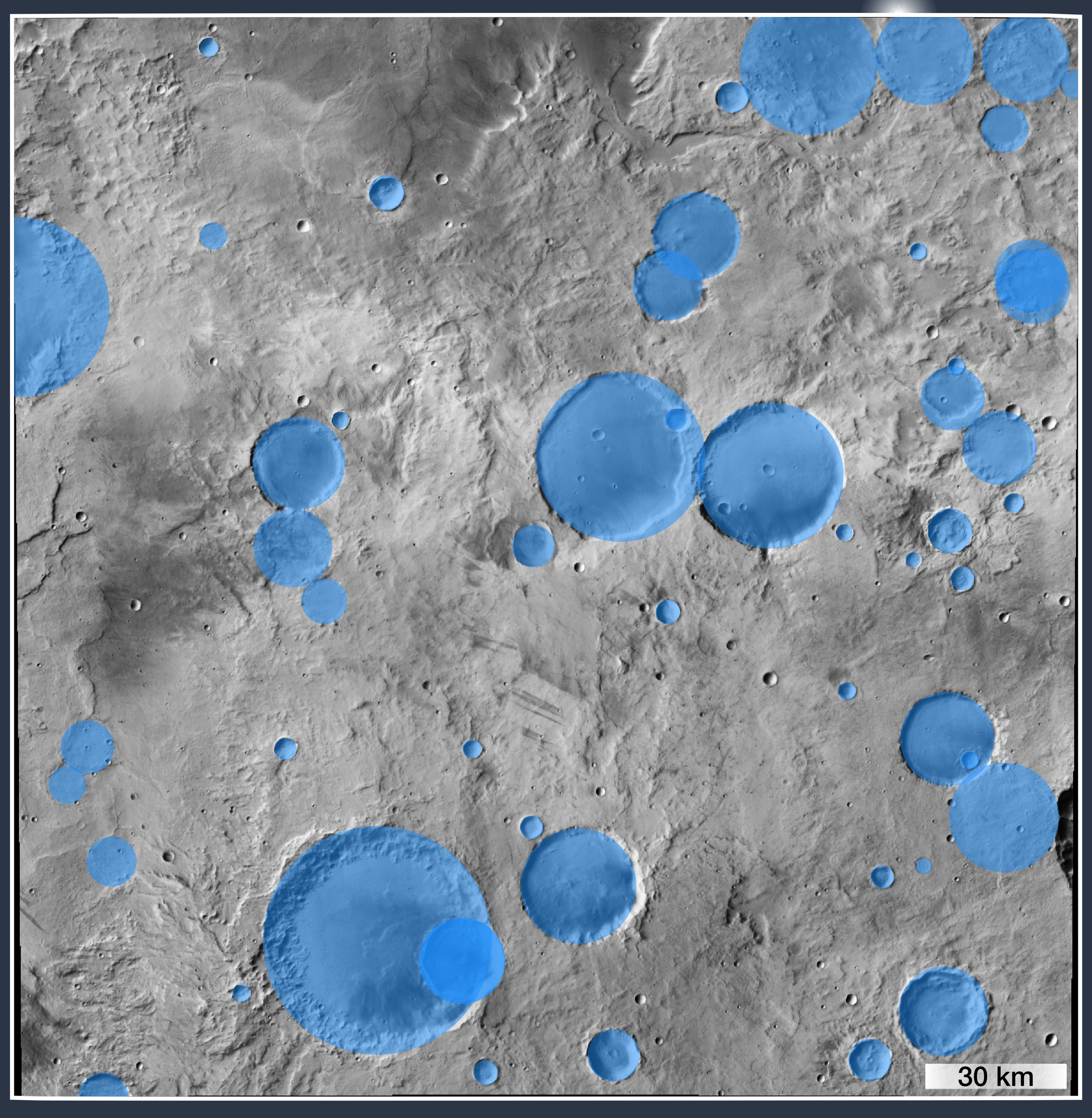

Fig 4. Inferences made on a 4x4° region (4°E, 16°S) in a CTX image

Results

In the end we applied our detection model to a 4°x4° quadrangle from the CTX mosaic and we have shown that our detector is able to detect craters in a satisfying way [7]. Our detector have an average precision score @ IoU = 0.5 of 0.8. It means that when a detection occurs, the probability that this detection is correct is around 80%. We also have a sensitivity score of ~ 0.7 which means that the probability that a ground truth crater will indeed be detected is around 70%

Conclusion and perspectives

We have successfully developped a crater detection tool using deep learning methods. Some improvement :

- Classification
- Mask-RCNN
- Adaptability on other bodies
- Datation

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