Automatic crater classification

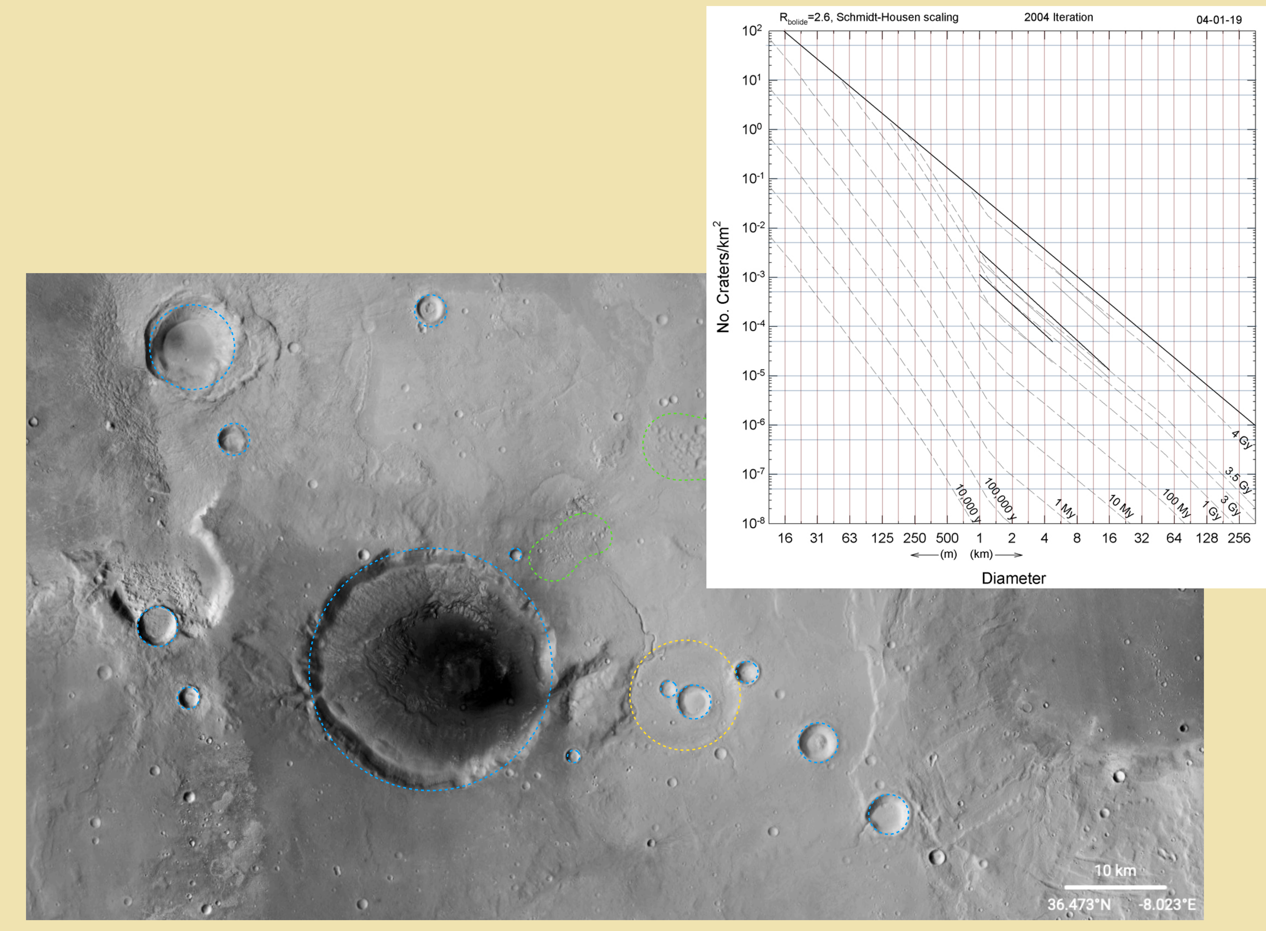
L. MARTINEZ[1,★], F. SCHMIDT[1,2], F. ANDRIEU[1], M. BENTLEY[3]

1 : Université Paris-Saclay, CNRS, GEOPS, 91405, Orsay, France
2 : Institut Universitaire de France
3 : European Space Astronomy Centre, Camino Bajo del Castillo, s/n., Urb. Villafranca del Castillo, 28692, Villanueva de la Cañada, Madrid, Spain

★ leonard.martinez@universite-paris-saclay.fr

Introduction

Impact craters are essential markers for reconstructing the geological history of planetary surfaces [1]. On Mars, where no absolute radiometric dating has yet been conducted in-situ, the density of craters remains the main chronometer used for dating surface units [2, 3]. However, this method critically depends on the correct identification of **primary craters**, as **secondary craters** (formed by ejecta from a primary impact) and **ghost craters** (highly degraded or buried) must be excluded to **avoid significant overestimations of surface ages** [4]. As the identification of crater morphological features is still a long, repetitive, and subjective task when performed manually, the application of modern computer vision techniques has become more and more relevant. While automated crater detection has seen substantial progress in recent years thanks to deep learning and computer vision techniques [5, 6, 7], the classification of craters based on their morphology remains largely unexplored. Yet, such classification is essential to ensure both the validity of crater inventories and the robustness of derived age estimates.



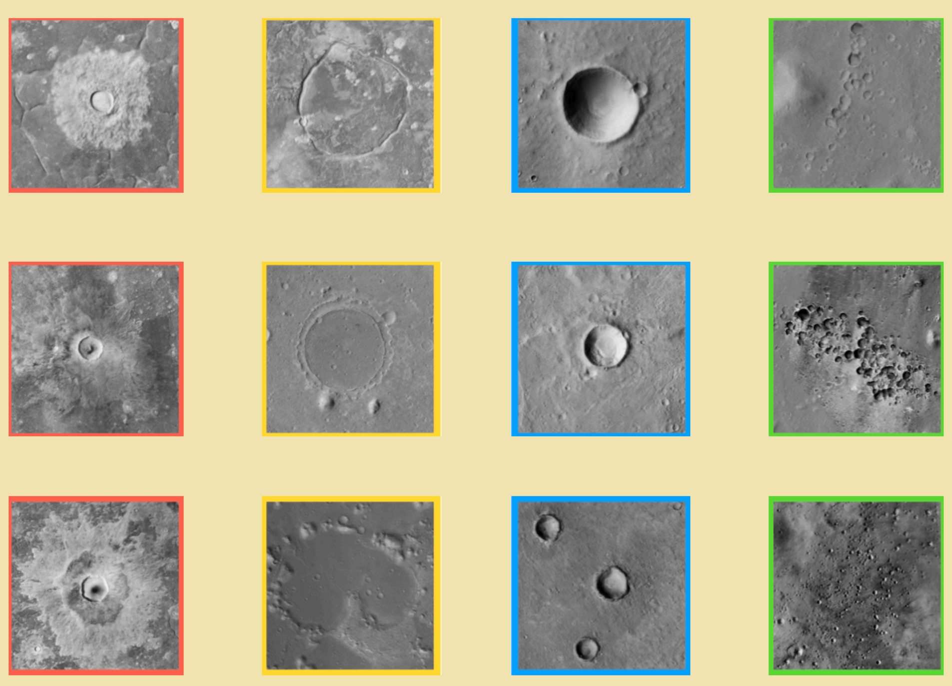


Figure1: Four different crater morphologies as define by **Lagain et al. (2021)** [4]. From left to right: *Layered (red)*, Ghost (yellow), *Regular* (blue) and *Secondary (green)*

Data

To train our classifier, we relied on the comprehensive work of **Lagain et al. (2021)** [4], which provides a **manually annotated catalogue of more than 376,000 craters** with a size superior at 1km in diameter into four morphological classes (See Figure.1): *Regular*, *Secondary*, *Ghost*, and *Layered*. **Image patches** centered on each crater are extracted from the **global CTX mosaic** [8], after reprojection in local stereographic coordinates to preserve the circular geometry of craters at high latitudes. To ensure robustness, we refine the crater locations and sizes using a circle detection algorithm based on the Hough transform [9]. This preprocessing step significantly improves the alignment between craters and image content, a critical requirement for effective supervised learning. In order to train our model, we used **34,000 classified craters**, divided in **train (28,000 crater)**, **validation (6,000 craters)** and we test it on a region which contain 45,000 craters.

Method

We trained a convolutional neural network classifier based on the **YOLOv11** architecture, using a balanced and augmented subset of the crater database. Each image patch is **resized** and **normalized**, and we apply tandard **data augmentation** strategies including rotations, flips, and artificial masking to simulate realistic artefacts in CTX images. The model outputs is a classification among the four crater classes describe previously. raining was conducted over **32 epochs** on a high-performance multi-GPU (8) server using a cross-entropy loss function and a cosine decayed learning rate schedule.

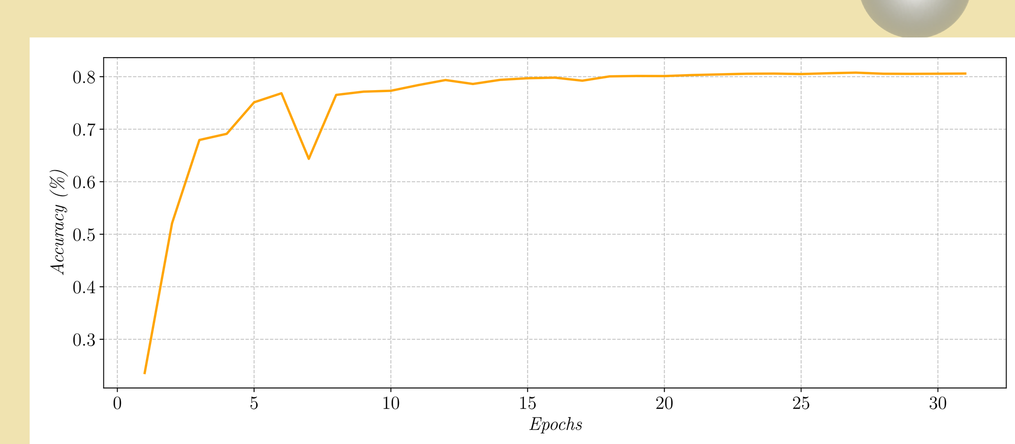


Figure2: Validation accuracy with respect to the training epochs

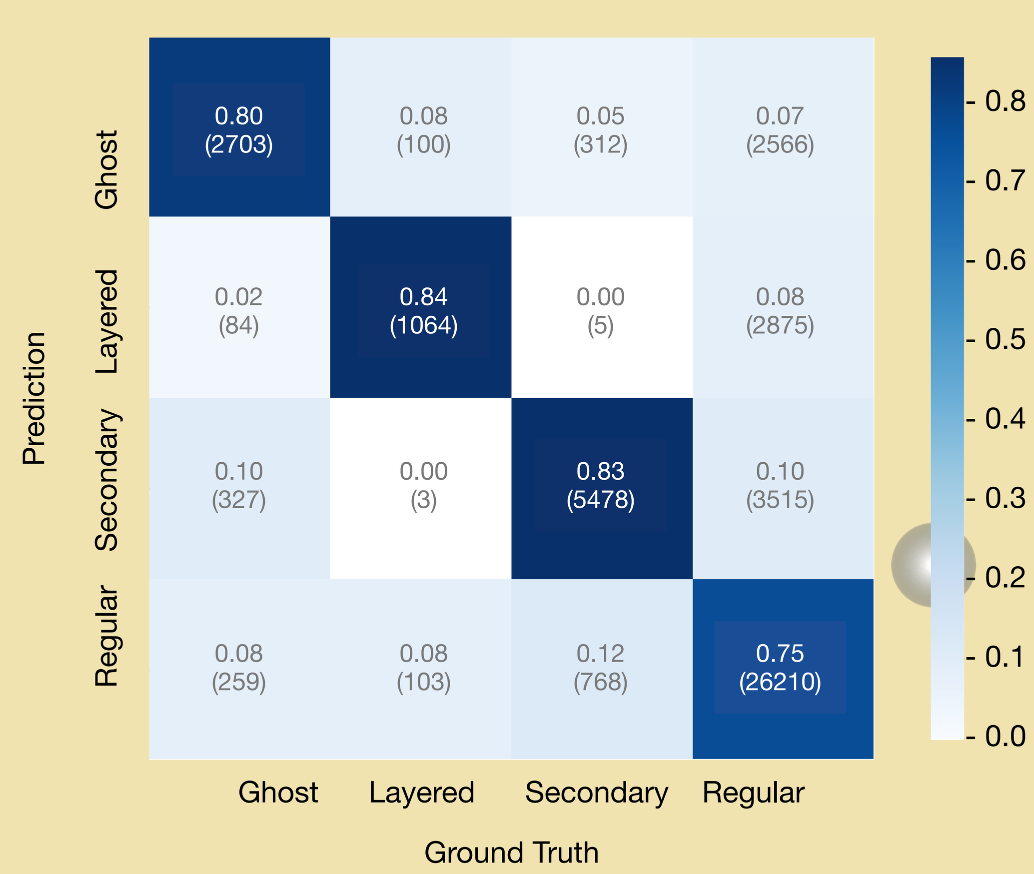


Figure3: Confusion matrix made on the test subdataset (45000 craters).

Results

The final model achieves a classification **accuracy** of over **80%** on a geographically diverse and independent test subdataset containing over 45,000 craters. The Figure3 shows the confusion matrix which gaves us a good insight as how the classification model performed. Performance remains consistent across latitudes. Figure4 shows the classification made on 4 example craters, showing excellent classification, including robustness to illumination conditions and image condition (corrupted data).

We also demonstrate the practical use of our classification model in the context of surface dating. By comparing cumulative crater size-frequency distributions (CSFD) before and after removing ghost and secondary craters, we show that automated filtering improves the coherence of the inferred ages with those expected from established crater chronologies.

Figure4: Example of 4 crater present in a test area. The prediction scores are written at the bottom of each images.

Conclusion and perspectives

We present a novel, scalable, and accurate pipeline for automatic crater classification, which complements existing detection models and provides a new tool for planetary surface dating. This study represents the first fully automated morphological classification of Martian impact craters using deep learning. Our results demonstrate the potential of AI-based approaches to improve crater-based chronostratigraphy, especially when applied systematically to global datasets. As a future work, we plan to extend the model to the Moon and Mercury using transfer learning, but also incorporate additional crater classes or features (e.g., central peaks, double-layer ejecta). Finally, the plan to refine existing Martian chronologies using the filtered crater populations.

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