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Lunar Crater Detection Using YOLOv8 Deep Learning
A Short Communication
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Abstract. In lunar exploration missions, the detection of lunar craters is essential for scientific inquiry, navigation, and terrain analysis. Conventional approaches for identifying craters depend on labor- and time-intensive manual inspection or semi-automated procedures. An effective and precise way to automate this procedure is through the use of deep learning algorithms. In this brief message, we introduce our implementation of the cutting-edge object detection method, YOLOv8, for the purpose of detecting lunar craters. The YOLOv8 architecture, which is well-known for its quickness and precision in object identification tasks, was employed. YOLO (You Only Look Once) predicts bounding boxes and class probabilities for several items in an image at once using a single neural network. We used a dataset of high-resolution lunar surface photos with crater annotations to train the YOLOv8 model.

Keywords. Lunar crater detection— YOLOv8—deep learning—object detection—planetary science—space exploration.

1. Introduction

Understanding the surface processes and geological past of planets, moons, and other celestial bodies has long depended on the study of craters. Craters act as geological archives, holding onto proof of past geological activity and impact events spanning billions of years Yue *et al*. (2023). On the other hand, scientists find it extremely difficult to manually locate and catalog craters in large-scale planetary photographs. A promising way to automate crater detection and analysis has emerged with the rise of deep learning, an artificial intelligence subfield. This would greatly improve the efficiency and accuracy of planetary exploration missions Lee & Hogan (2021).

1.1 *Fundamentals of Deep Learning:*

Deep learning LeCun *et al*. (2015) has become a potent paradigm for resolving challenging pattern recognition tasks because it draws inspiration from the structure and operation of the human brain. Artificial neural networks Yegnanarayana (2009), especially convolutional neural networks (CNNs) Aghdam & Heravi (2017), which are excellent at extracting hierarchical features from unprocessed data, are the brains of deep learning. Multiple layers of linked neurons make up CNNs, and each layer extracts progressively more abstract properties from the input data. CNNs can automatically identify patterns and features from planetary images that are relevant to crater detection through a process called training Wu (2017).

1.2 *Understanding YOLOv8:*

YOLOv8, a state-of-the-art deep learning model, revolutionizes crater detection in planetary science. By harnessing real-time object detection capabilities, YOLOv8 automates the identification of craters from high-resolution planetary images. Its efficiency and accuracy enable rapid processing of vast datasets, providing invaluable insights into the geological history and surface dynamics of celestial bodies like the Moon and Mars. YOLOv8's methodology involves data collection, annotation, model training, and inference, culminating in robust crater detection with high precision and scalability Kang & Kim (2023). Challenges such as generalization and data limitations persist, but ongoing research aims to overcome these hurdles, paving the way for enhanced understanding and exploration of planetary surfaces. Jocher *et al*. (2023)

2. Methodology:

The methodology for crater detection using YOLOv8 involves several key steps:

2.1 *Data Collection:*

Having access to high-quality labeled datasets is essential for the effectiveness of deep learning-based crater detection. Here in this article we have used the DEM images of Terrain Mapping Camera-2 Chowdhury *et al.* (2020). Terrain Mapping Camera or TMC 2 is to map the lunar surface in three dimensions. From the 100 km altitude orbit, the camera will survey the lunar surface with a 20 km swath width and a 5 m resolution in the panchromatic spectral range between 0.5 and 0.8 microns. The training data and validation of the training was done on Impact Moon Craters (LU3M6TGT) dataset Grassa (2023).

2.2 *Training:*

Training a deep learning model Keskar *et al.* (2016) for crater detection involves feeding it with labeled examples of craters and non-craters Tewari *et al.* (2023), allowing the model to learn discriminative features that distinguish between the two classes. In order to reduce the difference between its predictions and the ground truth labels in the training data, the model iteratively modifies its internal parameters during training Lee (2019).

2.3 *Validation:*

Upon being trained the model is evaluated with a separate validation dataset Samek *et al.* (2017). The metrics which are accuracy, precision Miller (1975), recall Junker *et al.* (1999) and F1 score Flach & Kull (2015) Yacouby & Axman (2020) are generally used for assessing the model's ability for carrying out the prediction.

3. YOLOv8 structure:

Four major parts make up the YOLOv8 network architecture: the input, the feature enhancement (Neck) Xu & Wu. (2021), the backbone network, and the decoupling head (Head) Lin *et al.* (2023). Important improvements on the input side are adaptive grayscale filling, adaptive anchor frame computation, and mosaic data augmentation. YOLOv8 backbone network uses the lightweight CSPLayer_2Conv module in conjunction with the CSP (Cross Stage Partial) idea instead of the traditional C3 module. The widely used SPPF (Spatial Pyramid Pooling with Factorized convolutions)Ji *et al.* (2022) module, which adds to the backbone network's strong feature extraction capabilities, finishes the system. The separation of the prediction and regression branches is the responsibility of the decoupling head. Both the category and localization components are used in the loss computation in the regression branch. The BCE (Binary Cross Entropy) loss function Ruby & Yendapalli (2020) is used in the adoption of VFL Loss (Varifocal Loss) for category loss Liu *et al.* (2023). The components of loss associated with localization are the CIOU (Complete IOU) Zheng *et al.* (2020) and DFL (Distribution Focal Loss) **?**. The network architecture Wu & Yolo-se (2023) is illustrated in Figure 1

4. Evaluation from Metrics

In order to evaluate the prediction models we perform the test for Precision-Confidence curve and F1 Confidence tests.

5. Experimental Results

In order to understand how our model has worked we compare the predicted images with actual images from TMC-2. They are followings:

6. Advantages of YOLOv8:

- Real-time Detection Talib *et al.* (2024): YOLOv8 is capable of processing images in real-time, making it suitable for applications where speed is critical, such as planetary exploration missions.
- High Accuracy Talib *et al.* (2024) : YOLOv8 achieves high accuracy in object detection tasks, enabling reliable identification of craters and other features on planetary surfaces.
- Scalability: YOLOv8 can be scaled to handle large datasetsMa *et al.* (2024) Zhang *et al.* (2023) and diverse environmental conditions, making it adaptable to different planetary exploration scenarios.

7. Challenges:

There are several problems to be addressed of using YOLOv8:

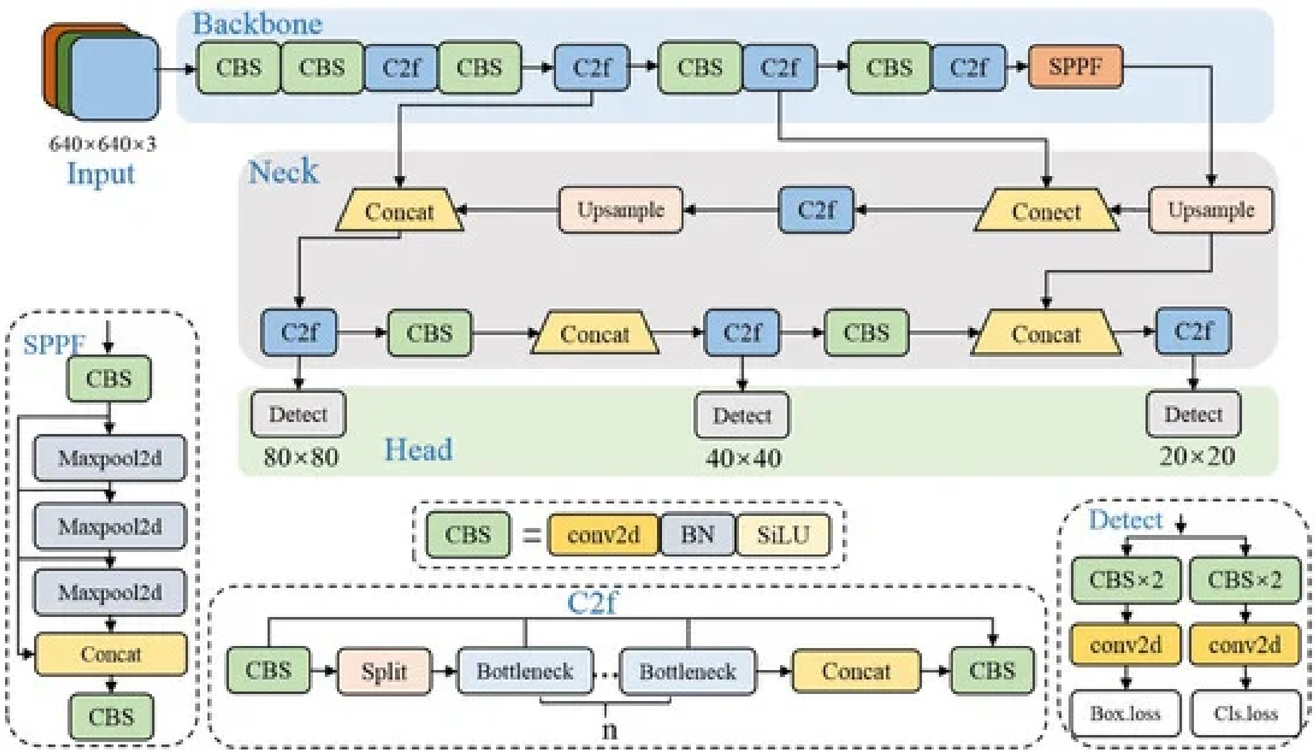

Figure 1. YOLOv8 architecture

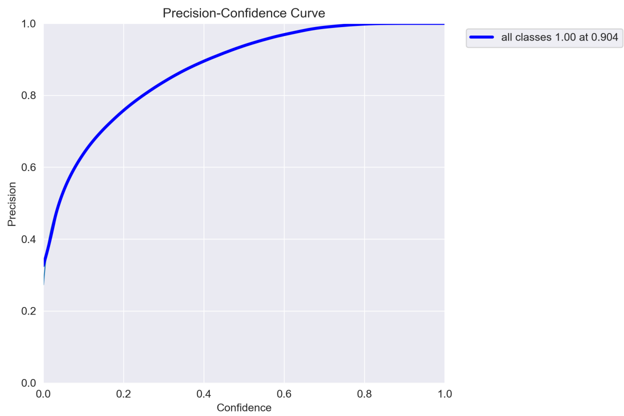

Figure 2. Precision Confidence Curve

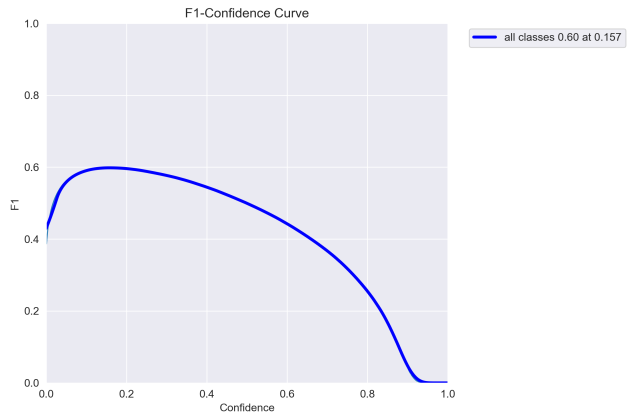

Figure 3. F1-Confidence Curve

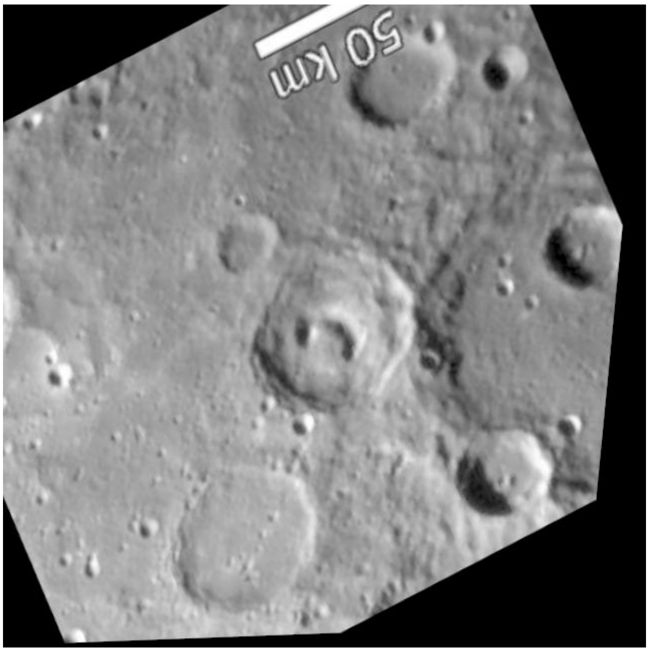

Figure 4. 1st Actual Image

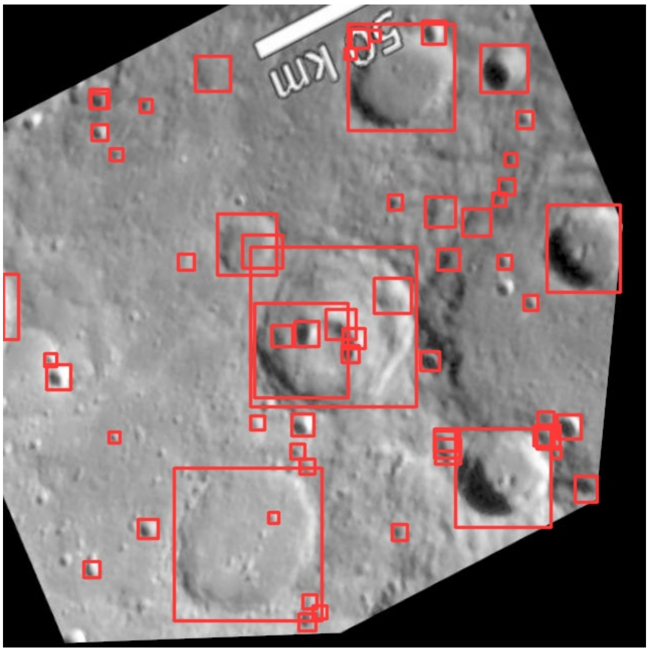

Figure 6. 1st Predicted Image

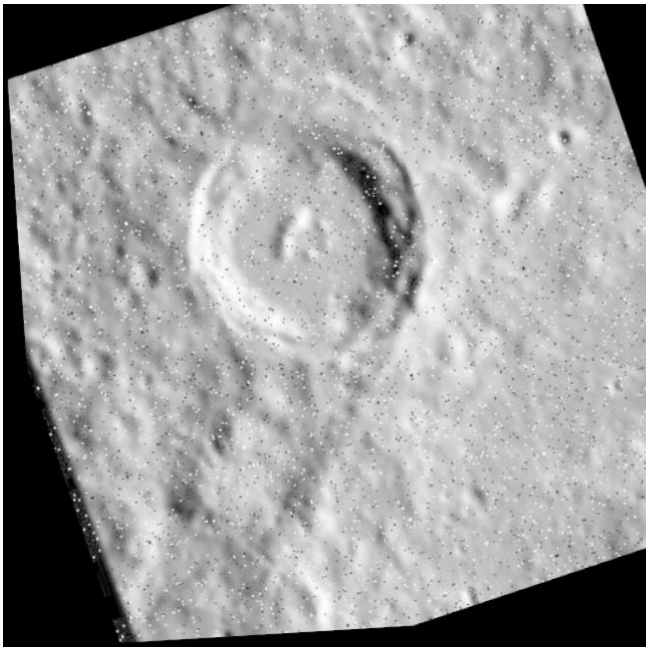

Figure 5. 2nd Actual Image

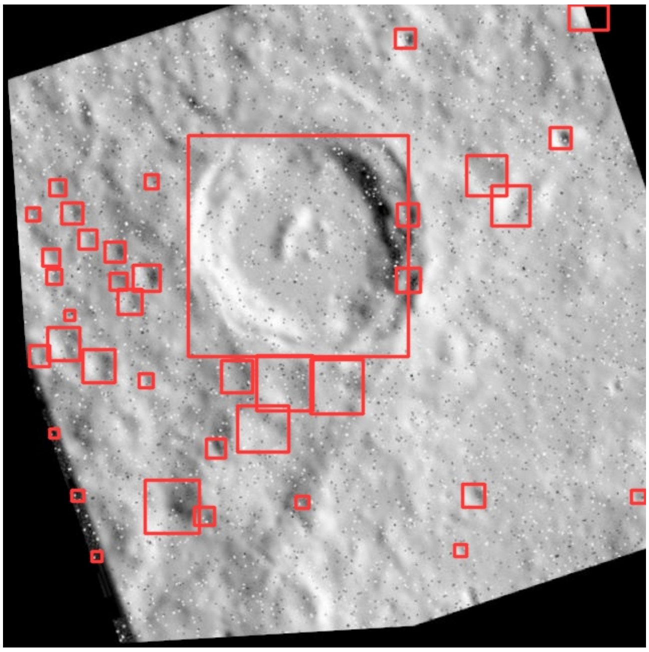

Figure 7. 1st Predicted Image

- Generalization: Ensuring the model's ability to generalize Farooq *et al.* (2023) across different planetary surfaces and environmental conditions.
- Robustness: Enhancing the model's robustness Bak *et al.* (2023) to variations in illumination, resolution, and surface features.
- Data Limitations: Addressing the scarcity of labeled data for training and validating the YOLOv8 model Soylu & Soylu (2023), particularly for less-explored celestial bodies.

8. Conclusion

Crater detection using deep learning represents a transformative approach to planetary science, enabling automated and accurate analysis of celestial surfaces at unprecedented scales. By harnessing the power of artificial intelligence, scientists can unlock the secrets hidden within planetary landscapes, unraveling the mysteries of our solar system's geological past and informing future exploration endeavors. As deep learning continues to evolve, the journey towards understanding the cosmos through crater detection promises to be both exciting and enlightening. By providing an overview of crater detection using YOLOv8 Suwinski *et al.* (2024), this article aims to inspire further exploration and innovation in the intersection of deep learning and planetary science, paving the way for new discoveries and advancements in our quest to unravel the mysteries of the cosmos.

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