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A Comprehensive Article on Deep Learning-Based Lunar Crater and Boulder Detection

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ABSTRACT

Exploring the lunar surface is key to understanding the Moon's geological history and planning future missions. Key surface features like craters and boulders provide valuable insights into the Moon's composition, age, and dynamic processes. This study presents an automated system for detecting and analysing these features using dual YOLO (You Only Look Once) models. YOLO's real-time object detection capability improves the speed and accuracy of crater and boulder identification in high-resolution lunar images, replacing labour-intensive manual methods. To enhance precision, segmentation models like U-Net are incorporated, offering pixel-level accuracy. This allows for more precise boundary detection, especially for overlapping or closely spaced features. U-Net's segmentation complements YOLO's object detection by providing more detailed pixel-wise classification. Additionally, Generative Adversarial Networks (GANs) are used to overcome the challenge of limited labelled data. GANs generate realistic synthetic lunar surface images, expanding the dataset and improving the robustness and accuracy of both YOLO and segmentation models. Preprocessing images, edge detection for feature extraction, and the application of methods such as thresholding and the Hough Transform are all part of the methodology. To classify and show the traits that have been recognized, the system additionally incorporates post-processing procedures. Our work offers a scalable and reliable method for lunar surface investigation by integrating and expanding upon previous studies. The results provide important information for scientific research and mission planning, with important ramifications for future lunar exploration missions. By showing that automated lunar feature detection is feasible, this effort paves the way for further explorations of the Moon's surface.

Keywords: *Artificial Intelligence, Boulders, Craters, Deep learning, GAN, Lunar object detection, Scatters, Segmentation, YOLO.*

1. Introduction

The exploration and study of the lunar surface are crucial for advancing our

understanding of the Moon's geological history and its potential for future exploration missions. The detection and analysis of surface features, such as craters and boulders, play a vital role in this endeavour. Craters (Fig. 1.1), formed by the impact of meteoroids, provide insights into the age and composition of the lunar surface. Boulders (Fig. 1.2), on the other hand, can indicate geological processes such as erosion, impact events, and surface regolith movement.

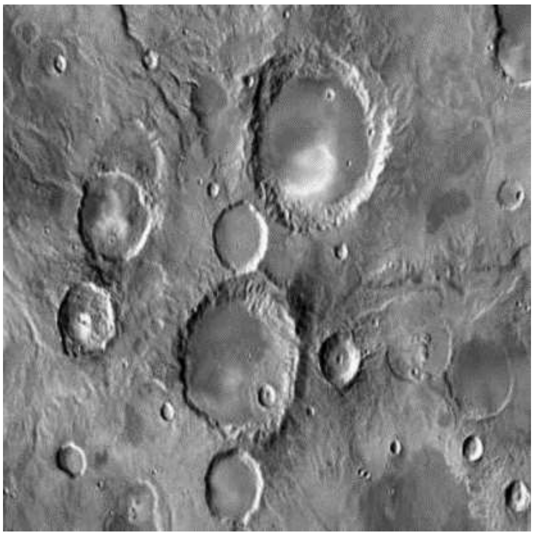

Fig. 1.1 Craters

Fig. 1.2 Boulders

In this project, we focus on developing an automated system for detecting and analyzing craters and boulders on the lunar surface using advanced computer vision techniques. Specifically, we leverage state-of-the-art object detection models, YOLO (You Only Look Once), to accurately identify and classify these features from lunar images. The ability to automatically detect and characterize these features can significantly enhance lunar research by providing detailed data for scientific analysis and mission planning.

Understanding the moon's surface and organizing space missions depend on the detection of lunar craters and boulders. While traditional approaches require human intervention and take a lot of time, deep learning provides precise, automated answers. By categorizing pixels, segmentation methods like U-Net assist in identifying and separating craters and rocks from the lunar surface. By producing realistic photographs of the lunar surface, Generative Adversarial Networks (GANs) improve detection even more while simultaneously increasing data availability and quality. When combined, these methods greatly improve the speed and accuracy of lunar feature detection.

This report presents the methodology, implementation, and results of our system for crater and boulder detection. We discuss the use of dual YOLO models to independently detect craters and boulders, the integration of these models into a unified framework, and the subsequent analysis of the detected features. In addition to YOLO, we incorporate segmentation models, such as U-Net, to enhance pixel-level accuracy in detecting and delineating the boundaries of craters and boulders. Furthermore, we utilize Generative Adversarial Networks (GANs) to augment the dataset and generate realistic lunar surface images, improving detection performance. Additionally, we explore the implications of our findings for lunar science and future exploration missions.

The objective of this project is not only to demonstrate the feasibility of automated lunar feature detection but also to contribute valuable data that can be used by researchers and engineers in the field of lunar exploration. By automating the detection process, we aim to reduce the time and effort required for manual analysis, allowing for more efficient and comprehensive studies of the Moon's surface.

2. Literature Review

Traditional lunar crater and boulder detection systems have relied heavily on manual and heuristic methods for identifying and classifying geological features. These methods often involve manually defining crater and boulder characteristics based on optical image analysis and morphological techniques

Sr. No.	**Title of the Paper**	**Year of Publication**	**Algorithm/ Techniques/ Tools used**	**Accuracy/ Result Achieved**	**Remarks**
1.	Automated Mapping of Boulders on the Lunar Surface with Deep Learning to Determine Crater Ages	2024	Automatically maps boulders in LRO NAC images.	Detections align well with manual mappings and Diviner rock abundance data.	Automated method offers quicker and consistent boulder mapping.
2.	Automated Boulder Counting: Deep Learning for Boulder Detection and Height Estimation,	2023	Convolutional Neural Network (CNN)	Effective in detecting boulders down to the subpixel level.	Improves boulder detection in low-resolution imagery through shadow analysis.
3.	Analysis of boulders population around a young crater using very high-resolution image of Orbiter High Resolution Camera (OHRC) on board Chandrayaan-2 mission.	2022	Image processing and power law fitting.	Extended identifiable boulders below 1 m, mapped over 2000 boulders with fitting coefficients matching literature.	OHRC's high resolution captured small features and illuminated shadows, aiding boulder distribution studies.
4.	Automated Lunar Crater Identification with Chandrayaan-2 TMC-2 Images using Deep Convolutional Neural Networks	2024	U-Net with ResNet50 backbone.	60.95% on unannotated data; 66.91% on annotated data.	Effective for automated lunar crater detection, promising further accuracy improvements with better annotation and more data.
5.	Artificial intelligence in remote sensing geomorphology—a critical study.	2023	CNNs detect lunar boulders with tracks from orbiter images.	CNNs identified <20% of boulders found by human analysts.	Image selection and lack of topographic data affected accuracy.
6.	Boulder distribution, circular polarization, and optical maturity: A survey of example lunar polar terrains for future landing sites.	2023	Correlation and spatial distribution analysis.	Correlation coefficients (e.g., CPR and surface roughness correlation is 0.48).	Weak correlation between boulder density and CPR/OMAT .
7.	Analytic rock abundance distributions and their application to spacecraft landing hazards.	2023	Random rock field generation.	33% parameter convergence.	Natural-looking rock distribution.

In the study of Shintaro et. al[8] Crater classification is a fundamental task in planetary science, particularly in the study of lunar geology. Accurate classification and identification of craters are essential for understanding the history of the Moon's surface, including the frequency and scale of impact events. Traditionally, Digital Elevation Models (DEMs) have been employed for crater classification due to their ability to provide topographical data. However, DEMs are often limited by their resolution, which can hinder the detection and classification of small craters.

The work of Prieur et. al[9] presents that the Boulders, formed through diverse geological processes, provide valuable insights into planetary surface dynamics, including potential hazards for spacecraft landings. Traditionally, mapping boulders over large areas is labor-intensive, restricting both the extent and statistical robustness of boulder characterization. To address this challenge, they developed an automated approach for boulder detection and characterization using an instance segmentation neural network, Mask R-CNN. The system, BoulderNet, was trained on a comprehensive dataset comprising over 33,000 boulders across more than 750 image tiles from Earth, the Moon, and Mars.

Yutong et. al[10] presents Traditional lunar crater detection methods often rely on manually defining crater features and using morphological characteristics, resulting in limited precision and slower retrieval speeds. These traditional algorithms are labor- intensive and struggle with accurately extracting crater features, leading to inefficiencies. To address these issues, recent advancements have leveraged deep learning techniques, particularly the U-Net model for image segmentation.

The proposed Craters Detection Algorithm presented by Nur Diyana et. al[11] focuses on reliable topography- based crater detection using a combination of real image (optical image) analysis and morphological image analysis. The algorithm is designed to operate in a sequence of stages to achieve satisfactory results, assuming the sun elevation angle is known. The process begins with analyzing a 2-D optical image.

Ottaviano et. al[12] presents the methodology described utilizes the RetinaNet convolutional neural network (CNN) architecture, specifically with a ResNet50 backbone, for detecting and mapping lunar features. This approach has been previously validated in lunar machine-learning studies, demonstrate its effectiveness in handling complex geological mapping tasks. The network's capability to identify and categorize various lunar features, such as fractured boulders and rocky craters, has been well-documented in related research.

While effective to some extent, these approaches suffer from several significant drawbacks. The reliance on manual labeling and feature extraction can lead to inconsistencies and inaccuracies in detection, particularly when dealing with largescale lunar imagery. The computational efficiency of these methods is also limited, resulting in slow processing times. Additionally, traditional methods often struggle with detecting and distinguishing between a wide variety of geomorphic features, such as fractured boulders, craters, and impact melt deposits, due to their reliance on fixed morphological criteria. The manual analysis required to sort and review detected features further exacerbates these issues, making systematic analysis challenging and time-consuming.

3. Methodology

The proposed system leverages a YOLO-based model for lunar crater and boulder detection, offering a modern solution to the limitations of traditional methods. YOLO (You Only Look Once) is known for its real-time object detection capabilities and high accuracy, making it well-suited for analysing large volumes of high-resolution lunar imagery. The YOLO-based model efficiently detects and classifies various geological features, including craters and boulders, by processing images in a single pass and generating bounding boxes around detected objects. This approach significantly improves processing speed and accuracy compared to traditional methods. Additionally, YOLO's ability to handle multiple object types and sizes enhances its effectiveness in distinguishing between different geomorphic features. By automating the detection and classification process, the YOLO-based system reduces manual labor, increases the consistency of results, and facilitates the systematic analysis of extensive lunar datasets. This advancement offers a more efficient, accurate, and scalable solution for lunar surface exploration and analysis.

To properly define the edges of craters and boulders, the system integrates a segmentation model that conducts pixel-wise categorization. Segmenting the surface characteristics facilitates a more comprehensive examination, which is especially helpful in areas where object borders are ambiguous or overlap. By supplementing the bounding boxes produced by YOLO with pixel-level segmentation masks, the segmentation model improves detection accuracy. Moreover, artificial lunar surface pictures are produced by a Generative Adversarial Network (GAN) to supplement the training data. By adding a variety of actual instances to the dataset, this makes the model more resilient and helps overcome the issue of insufficient labelled data. The YOLO and segmentation models perform better thanks to the GAN- generated data since it increases the variety of the training set.

Here is the detailed view of how the objects are identified and trained.

3.1 Input Image:

The process begins with acquiring high-resolution images of the Moon's surface. These images serve as the raw data for subsequent analysis and feature extraction.

3.2 Preprocessing:

- **Grayscale Conversion:** The input colour images are converted to grayscale to simplify the data and focus on intensity variations rather than colour.
- **Normalization:** Pixel values in the grayscale images are normalized to a common scale, improving the consistency and performance of the feature extraction algorithms.
- **Noise Reduction:** Various noise reduction techniques, such as Gaussian blur, are applied to minimize artifacts and enhance the quality of the images for more accurate detection.

3.3 Feature Extraction:

- **Edge Detection:** Algorithms like the Canny edge detector is used to identify the edges of craters and boulders by detecting significant changes in intensity. This helps in highlighting the boundaries of features.
- **Dilation:** The detected edges are dilated to make the features more pronounced and connect fragmented edges, aiding in more accurate detection of craters and boulders.

3.4 Crater & Boulder Detection:

- **Hough Transform:** This technique is employed to detect circular shapes within the image, which helps in identifying craters. The Hough Transform maps the detected edges to a parameter space where circular shapes can be identified.
- **Thresholding:** A thresholding method is used to differentiate between the detected features and the background. It converts the processed image into binary form, where features of interest are highlighted against a black background.
- **U-Net:** It is an architecture for convolutional neural networks (CNNs) that is specifically utilized for picture segmentation. Built upon a U-shaped encoder or decoder construction, it is here intended to be both quick and accurate.

3.5 Post-processing:

- **Bounding Boxes:** The system draws bounding boxes around detected craters and boulders to localize and outline these features clearly in the image.
- **Labelling:** Each bounding box is labeled according to the type of feature it contains (e.g., crater or boulder), facilitating easy identification and analysis of the features.

3.6 Output Image Generation*:*

The final step involves generating an output image that displays the detected craters and boulders with bounding boxes and labels. This image provides a visual representation of the detected features, ready for further analysis or presentation.

The method decreases human effort, improves consistency, and permits a more in-depth examination of large lunar datasets by automating the detection, segmentation, and data augmentation procedures. A very effective, precise, and scalable method for exploring and analysing the lunar surface is provided by the combination of YOLO, segmentation, and GAN models.

4. Conclusion

In this study, we have introduced a sophisticated dual YOLO model approach for the automated identification and analysis of lunar surface features, particularly craters and boulders. Compared to previous methods, which frequently rely on labour-intensive, inconsistent, and prone to error manual processes and heuristics, the implementation of this system shows a notable improvement. Deep learning methods, especially YOLO, improve the efficiency of lunar surface exploration by enabling accurate, real-time feature recognition and classification.

The proposed method ensures an organized approach to detecting and categorizing lunar features using preprocessing, feature extraction, and post-processing processes. In addition to speeding up the feature identification process, this method increases the accuracy of the output, yielding useful information for mission planning and scientific study.

Our findings provide a scalable and reliable system that may be modified for next lunar exploration missions, adding to the increasing body of work on automated lunar feature detection. This work establishes the viability of automated detection, creating new opportunities for thorough surface analysis and ultimately aiding in the design and implementation of future lunar missions. Incorporating these automated methods is essential to improving our knowledge of the Moon's geological past and future exploration possibilities.

5. Future Scope

The future scope of this research is expansive, with potential advancements in lunar exploration and beyond. Integrating multi-spectral imagery and Digital Elevation Models (DEMs) could enhance the detection of subsurface structures and provide detailed topographical analysis. Real-time processing capabilities could be developed for lunar missions, increasing the autonomy of rovers and landers during exploration. The methodologies presented can be adapted for other celestial bodies like Mars and asteroids, expanding their applicability in planetary science. Future work could explore advanced deep learning models, such as transformer- based architectures, to further improve detection accuracy and efficiency.

Additionally, creating and sharing large-scale annotated lunar datasets would encourage community-driven improvements and foster collaboration. The system could also be extended to automated mapping and hazard detection, essential for ensuring safe landings and exploration. Combining surface feature detection with geological and seismological data would offer deeper insights into the Moon's interior and history.

Finally, developing user-friendly interfaces and visualization tools would make the system accessible to a wider audience, including non-experts, enhancing its utility for custom analyses and mission planning. These advancements would significantly contribute to lunar science and future exploration missions.

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