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Automatic Detection of Craters and Boulders from OHRC Images Using Deep Learning

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ABSTRACT

The development of an automated system for detecting craters and boulders in high-resolution images from the Orbiter High Resolution Camera (OHRC) using deep learning techniques is crucial for advancing planetary exploration. This study introduces a novel integration of the YOLOv8 object detection algorithm with the Segment Anything Model (SAM) for segmentation, ensuring accurate and efficient identification of geological features. Unlike previous approaches that rely on either object detection or segmentation alone, our method combines real-time object detection with precise segmentation, achieving superior boundary accuracy and detection speed. Leveraging images from the Chandrayaan-2 mission, the proposed system is optimized for scalability and responsiveness in planetary surface analysis. This automation minimizes human involvement, reduces errors, and significantly enhances detection reliability. Furthermore, the ability to process large datasets with improved precision provides new insights into the distribution and morphology of craters and boulders. This contribution supports planetary research by addressing limitations in detection accuracy and efficiency found in prior methodologies, thereby delivering fast and reliable data for scientific analysis and future exploration missions.

Keywords— Deep Learning, Plant Nutrient Deficiency, Image Classification, Convolutional Neural Networks (CNN), Transfer Learning, Precision Agriculture

I. INTRODUCTION

Ensuring agricultural Over the past few years, planetary exploration missions led by organizations such as NASA, ISRO, and various international space agencies have generated an unprecedented volume of high-resolution data from the surfaces of the Moon, Mars, and other celestial bodies. Missions including Chandrayaan-1 and 2, the Lunar Reconnaissance Orbiter (LRO), and Chang'E have provided detailed imagery that is indispensable for analyzing surface features such as impact craters and boulders. These features not only serve as key indicators of a planet's geological history and surface evolution but also play a critical role in selecting safe landing sites for future missions.

The accumulation of vast datasets, however, has far outpaced the ability of human operators to manually analyze and interpret the imagery. Traditional processing methods and standalone algorithms, which often focus solely on object detection or segmentation, struggle to manage the complexity and diversity of the data. These methods typically suffer from inaccuracies when addressing overlapping or irregularly shaped geological features. Moreover, many existing approaches face challenges in maintaining the required processing speeds and scalability across varied planetary terrains. Consequently, there is a clear and pressing need for an automated system that can deliver real-time processing, high precision, and the adaptability to handle diverse datasets efficiently.

To address these challenges, our study proposes an innovative approach that integrates the real-time object detection capabilities of YOLOv8 with the advanced segmentation performance of the Segment Anything Model (SAM). YOLOv8 is recognized for its state-of-the-art performance in fast and reliable object detection. Its lightweight yet robust architecture is particularly well-suited for handling large-scale planetary datasets, enabling the rapid identification of craters and boulders with high confidence. On the other hand, SAM has been developed to excel in the segmentation domain, offering highly accurate boundary delineation even for objects that overlap or exhibit complex structures. By combining the capabilities of YOLOv8 and SAM, our method is designed to overcome the limitations of earlier approaches by providing simultaneous detection and segmentation with unprecedented accuracy and speed.

The integration of these two models is demonstrated through the processing of high-resolution imagery from the Optical High-Resolution Camera (OHRC) onboard Chandrayaan-2. This instrument captures images that reveal intricate details of the lunar surface, making it essential to have an automated system that reduces human intervention while improving analysis accuracy. The fusion of YOLOv8 and SAM not only enhances computational efficiency and detection precision but also minimizes potential errors, thereby enabling more robust scientific insights into planetary surface processes.

By automating the detection and segmentation process, our system significantly reduces the workload on human operators and allows for rapid, error-resistant analysis of vast amounts of data. This is particularly beneficial when managing the ever-growing datasets obtained from contemporary space missions, where both speed and accuracy are critical for timely mission planning and execution.

In summary, our study presents a cutting-edge solution aimed at overcoming longstanding challenges in planetary surface analysis by integrating YOLOv8 and SAM. The proposed method bridges the gap between detection and segmentation, ensuring high performance across diverse planetary terrains, and stands as a promising advancement for future exploration missions. This approach not only streamlines the data processing pipeline but also opens new avenues for in-depth geological analyses, ultimately contributing to safer and more informed decisions in planetary exploration.

II. RELATED WORKS

Recent advancements in automated crater detection for planetary surfaces have utilized sophisticated deep learning frameworks and domain adaptation strategies to differentiate genuine craters from unrelated geological formations. Progress in automation has been accelerated through the adoption of Convolutional Neural Networks (CNNs) and object recognition architectures, which enable precise identification and delineation of craters even in densely cluttered or overlapping terrain. Unsupervised domain adaptation techniques have emerged as particularly effective for transferring knowledge from data-rich domains to unexplored planetary regions lacking annotated datasets. Furthermore, the fusion of ensemble-based strategies, transfer learning principles, and hybrid architectures has achieved superior accuracy and computational efficiency compared to traditional approaches. This review systematically examines foundational algorithms and methodologies driving modern crater detection systems, highlighting pivotal developments while contextualizing persistent limitations and future research trajectories in the domain.

Zhang et al. [1] developed a deep learning-based unsupervised domain adaptation technique for detecting planetary craters. Their method tackles the challenge of domain shift by enhancing model generalization across different planetary datasets. By incorporating adversarial learning and feature alignment, their approach improves crater detection accuracy while reducing dependence on labeled training data from the target domain. The results demonstrate that this method is effective in identifying craters on various planetary surfaces, making it a valuable contribution to planetary exploration and remote sensing.

Salih et al. [2] introduced an automated framework for detecting craters and estimating surface ages in the Moon's mare regions. Their approach merges machine learning-driven crater recognition with geological dating methods to evaluate the chronological development of lunar terrain. By systematically analyzing spatial density and distribution patterns of craters, the system generates critical insights into the Moon's surface evolution. The framework demonstrated exceptional detection precision, underscoring the importance of combining morphological characterization with statistical modeling for advancing planetary geology research.

Silburt et al. [3]. proposed a deep learning-based framework for lunar crater identification using Convolutional Neural Networks (CNNs). Their model was trained on thousands of planetary surface images, outperforming traditional template-matching and edge-detection methods. Their results showed a higher detection rate and reduced false positives, making CNN-based techniques more efficient for automated planetary surface analysis. The model achieved an accuracy of approximately 92% in crater detection.

Emami et al. [4]. introduced a hybrid crater detection approach that combined unsupervised learning algorithms with deep CNNs. Their technique integrated clustering-based feature extraction with deep learning, improving crater detection performance in remote sensing images. By leveraging both conventional image processing techniques and CNN-based detection, they reduced false positives and achieved an accuracy of around 94%. The study highlighted the importance of hybrid methodologies in enhancing crater identification robustness across varying lunar terrains.

Alshehhi and Gebhardt [5]. proposed a deep domain adaptation framework for detecting geological landmarks on Mars using high-resolution lunar satellite images. They employed a transfer learning approach to adapt lunar-based models for Martian geological feature identification. Their study demonstrated the potential of cross-domain learning in planetary exploration. The framework achieved a detection accuracy of approximately 90%, showcasing the effectiveness of domain adaptation techniques in remote sensing.

Zhu et al. [6]. applied YOLOv7-based object detection for lunar impact crater recognition, integrating multi-source data fusion to enhance detection performance. Their study demonstrated how real-time object detection models like YOLO can significantly improve the speed and accuracy of crater identification. The proposed YOLOv7 framework outperformed previous crater detection models, achieving an accuracy of 96%, making it a highly efficient real-time approach for planetary surface analysis.

Chatterjee et al. [7] developed a deep learning framework for lunar crater detection using YOLOv5, emphasizing real-time performance alongside detection reliability. Their architecture utilized convolutional neural network layers and anchor-based detection mechanisms to recognize craters of diverse morphologies in high-resolution lunar surface imagery. The researchers performed systematic optimization of hyperparameters, fine-tuning critical parameters including batch dimensions, learning rates, and non-maximum suppression criteria to enhance localization precision. The refined YOLOv5 implementation reached a 96.85% detection accuracy rate, surpassing conventional machine learning approaches and prior deep learning implementations across precision, recall, and processing speed metrics. This work validated the effectiveness of real-time-capable detection architectures for planetary science applications, highlighting their potential to support automated terrain mapping systems for upcoming lunar missions.

Duan et al. [8] introduced a Digital Elevation Model (DEM)-based crater detection technique using a Max Curvature Detection Method, designed to overcome the limitations of optical image-based detection in shadowed and low-contrast regions. Unlike deep learning-based models requiring labeled training data, this approach analyzed the surface curvature variations of the lunar terrain to accurately extract crater boundaries. The method employed multi-scale curvature analysis to differentiate between impact craters and non-crater geological features, ensuring high geometric accuracy in crater detection. The proposed system was evaluated on Lunar Reconnaissance Orbiter (LRO) DEM data, achieving a detection accuracy of 93.72% with minimal false positives. The study demonstrated the effectiveness of topographical feature extraction techniques in planetary geology, offering a reliable alternative for crater identification, particularly in cases where labeled datasets for deep learning models are unavailable.

Ouyang et al. [9] addressed the challenge of domain shift in medical image segmentation by introducing a causality-inspired augmentation framework designed to enhance model generalization using only single-source domain data. Their approach leverages randomized shallow network architectures to generate diverse intensity and texture transformations, improving adaptability to variations in medical imaging data. The authors highlighted how spurious correlations between anatomical structures in images could degrade cross-domain performance and countered this by implementing causal intervention techniques. These techniques independently resampled the visual characteristics of correlated objects to disrupt artificial associations. The framework was evaluated across three distinct cross-domain segmentation scenarios: multi-modal abdominal imaging (CT-MRI), cross-sequence cardiac MRI (bSSFP-LGE), and multi-center prostate MRI analysis. Experimental results demonstrated consistent performance gains compared to existing approaches when applied to new domains, underscoring the method’s efficacy in advancing generalizable solutions for medical image analysis.

Li et al. [10] introduced a feature augmentation technique aimed at enhancing domain generalization in machine learning models. Their approach involves adding Gaussian noise to feature embeddings during training, helping the model develop more generalized representations that are less dependent on domain-specific characteristics. Additionally, they iteratively estimate the class-conditional feature covariance matrix to better capture statistical variations across domains. This method functions as a domain randomization strategy by modifying features along intra-class and cross-domain variability axes. The proposed technique was tested on three widely used domain generalization benchmarks—Digit-DG, VLCS, and PACS—where it either matched or outperformed existing state-of-the-art methods. The study emphasizes the effectiveness of feature augmentation in improving model robustness across diverse and unseen domains.

Zhang et al. [11] introduced VarifocalNet (VFNet), an advanced object detection model that incorporates IoU-awareness to enhance both classification confidence and localization accuracy. Their method employs Varifocal Loss and a refined bounding box adjustment strategy to improve detection performance. Built upon the FCOS framework, VFNet demonstrated superior accuracy, achieving a state-of-the-art AP of 51.3 on the MS COCO dataset.

Wang et al. [12] proposed a robust object detection framework that leverages instance-level temporal cycle confusion to improve feature consistency across video frames. Their approach enhances detection stability by mitigating temporal inconsistencies, making it effective for real-world applications where object appearances vary over time.

Huang et al. [13] introduced Frequency Space Domain Randomization (FSDR), a domain generalization technique that manipulates the frequency components of images to improve model robustness across different domains. By altering image frequency distributions during training, FSDR enhances feature adaptability, reducing the impact of domain shifts.

RoyChowdhury et al. [14] presented a self-training-based adaptation method for object detectors, enabling automatic fine-tuning to new domains without requiring labeled target data. Their framework employs pseudo-labeling and iterative refinement to improve domain adaptation, demonstrating significant performance gains in cross-domain detection tasks.

Gao and Zhou [15] introduced a feature density-based terrain hazard detection method for planetary landing, leveraging high-resolution elevation data to assess surface safety. Their approach calculates local feature density variations to identify hazardous regions, such as steep slopes, rough terrains, or obstacles. By integrating density-based clustering algorithms, their method differentiates between safe and hazardous landing zones. The efficacy of this technique was validated on planetary surface datasets, demonstrating its capability to enhance autonomous hazard detection with high accuracy and computational efficiency. This work contributes to improving safe planetary landings by providing a robust terrain analysis framework.

Jung et al. [16] proposed a Digital Terrain Map (DTM)-based approach for selecting safe landing sites in planetary missions. Their method leverages high-resolution digital elevation models (DEMs) to analyze terrain features and identify potential hazards such as craters, boulders, and steep slopes. The approach involves surface roughness estimation, slope gradient analysis, and crater classification to assess landing safety. Additionally, they employ multi-criteria analysis for hazard evaluation, enabling real-time autonomous decision-making. The effectiveness of their approach was validated on simulated lunar and Martian terrains.

Liu et al. [17] introduced a real-time crater-based monocular 3D pose tracking method for planetary landing and navigation. Their approach utilizes crater detection as key landmarks to estimate the spacecraft’s position and orientation using a single camera. By integrating crater recognition with a robust pose estimation algorithm, their method improves localization accuracy in challenging planetary terrains. The system continuously tracks craters across image sequences to update the spacecraft’s pose, ensuring precise navigation and landing guidance. The effectiveness of this approach was validated through simulations and real-world lunar datasets, demonstrating improved robustness in feature-sparse environments.

Salih et al. [18] developed an automated crater detection algorithm to analyze planetary surface age through crater statistics. Their method involves detecting craters from high-resolution planetary images and estimating their size-frequency distribution to infer the relative age of the terrain. By leveraging photogrammetry and remote sensing techniques, they improve the accuracy of crater identification and classification. The proposed approach was validated on lunar and Martian surfaces, demonstrating its effectiveness in planetary geological studies and surface evolution analysis.

Jia et al. [19] introduced an automated framework for lunar crater identification based on deep learning methodologies. Their approach utilized a modified U-Net architecture—a convolutional neural network (CNN) specifically enhanced for semantic segmentation tasks—to precisely delineate craters in high-resolution lunar imagery. The study leveraged high-resolution terrain data captured by NASA's Lunar Reconnaissance Orbiter Camera (LROC), enabling detailed analysis of surface morphology. The refined model demonstrated the capability to identify craters down to 1 kilometer in diameter while achieving a detection accuracy rate of 93.4%. This work highlights the viability of deep learning architectures for extraterrestrial terrain mapping applications, offering valuable tools for lunar geological studies and mission planning.

Wang et al. [20] introduced a semivariogram-based approach to identify the multiscale spatial structure of lunar impact craters using remote sensing data. Their method employed spatial statistical analysis to examine crater distribution patterns and quantify terrain roughness. By leveraging semivariogram models, they measured spatial correlations between craters, enabling more precise classification of crater morphology and size variations. This approach helped in distinguishing between primary and secondary craters by analyzing their spatial heterogeneity. Additionally, their study highlighted the significance of geostatistical techniques in understanding lunar surface evolution and impact processes. The method was validated using high-resolution lunar images, demonstrating its effectiveness in crater detection and characterization across different scales. Their findings contribute to automated planetary surface analysis and improve crater mapping accuracy for future exploration missions.

Bickel et al. [21] proposed a deep learning-driven approach for detecting and mapping rockfalls on the Martian surface using high-resolution remote sensing imagery. Their method utilized a convolutional neural network (CNN) trained on Mars Reconnaissance Orbiter (MRO) images to identify rockfall deposits with high accuracy. By analyzing morphological characteristics and spatial distributions, they demonstrated the effectiveness of deep learning in automating planetary surface studies. The model was designed to distinguish rockfall events from other geological formations, improving the efficiency of hazard assessment and terrain analysis. Their study also emphasized the importance of training data augmentation to enhance model generalization across diverse Martian landscapes. The approach integrated image segmentation techniques to improve feature extraction, ensuring robust detection even in complex terrain conditions. Validation experiments showed that their method outperformed traditional manual mapping techniques, reducing processing time and increasing detection reliability. The findings highlight the potential of artificial intelligence in planetary geoscience, facilitating large-scale mapping of surface changes on Mars. This research contributes to the broader application of machine learning for planetary exploration, enabling automated detection of geological events with minimal human intervention. Their approach sets a foundation for future studies on rockfall dynamics and surface evolution, aiding mission planning and scientific investigations of Martian landscapes.

Miao et al. [22] introduced LCDNet, an innovative neural architecture optimized for lunar crater detection through Digital Elevation Model (DEM) data analysis. The framework employs deep learning architectures to systematically interpret elevation patterns in high-resolution lunar terrain datasets, enabling precise identification and categorization of craters. Trained on curated DEM imagery, the model enhances its capacity to recognize craters across diverse scales and morphological configurations. LCDNet integrates sophisticated feature extraction mechanisms and hierarchical scale processing to refine detection performance. Comparative evaluations revealed the method's superiority over classical crater detection algorithms, with marked improvements in both precision and recall metrics. Validation against standardized DEM benchmarks underscored the system's efficacy for autonomous lunar surface characterization, advancing capabilities in geological mapping and exploration mission design. This work represents a methodological leap in planetary science, offering scalable tools for automated terrain analysis critical to lunar research.

III. Tables

TABLE I. SUMMARY OF YOLO,CNN MODELS AND YOLOv5-BASED FRAMEWORKS FOR CRATER AND BOULDER DETECTION IN PLANETARY IMAGERY

Ref.	**Authors**	**Objective**	**Method**	**Key Findings**
[1]	Z. Zhang et al. (2023)	Detect craters using	UDA with deep learning models	Improved crater detection across different planetary datasets
[2]	A. L. Salih et al. (2017)	Crater detection and age estimation	Machine learning on lunar mare region images	Enhanced age estimation accuracy for lunar craters
[3]	A. Silburt et al. (2019)	Deep learning-based crater identification	CNN trained on lunar imagery	Higher accuracy in crater recognition compared to traditional methods
[4]	E. Emami et al. (2019)	Detect craters using unsupervised learning and CNNs	CNN and clustering algorithms	Effective crater detection without labeled datasets
[5]	R. Alshehhi et al. (2022)	Identify geological features on Mars using lunar image knowledge	Deep domain adaptation	Improved landmark detection using transferred knowledge
[6]	J. Zhu et al. (2023)	YOLO V7-based crater detection	YOLO V7 on multisource data	Real-time crater detection with high accuracy
[7]	S. Chatterjee et al. (2023)	Real-time crater detection using YOLO v5	YOLO v5-based object detection	Faster and more efficient crater detection

Ref.	Authors	Objective	Method	Key Findings
[8]	Q. Duan et al. (2024)	Detect craters using DEM data	Max curvature detection method	Robust crater detection using terrain data
[9]	C. Ouyang et al. (2023)	Improve domain generalization for medical segmentation	Causality-based domain generalization	Higher segmentation robustness in medical imaging
[10]	P. Li, D. Li, W. Li, et al.	Enhance domain generalization in object detection	Feature augmentation techniques	Improved model generalization for unseen domains
[11]	H. Zhang et al.	Improve object detection performance	IoU-aware object detection network	Enhanced localization accuracy
[12]	X. Wang et al.	Improve object detection robustness	Instance-level temporal cycle confusion	Better object detection in dynamic environments
[13]	J. Huang et al.	Domain generalization via frequency-space transformations	Frequency-based domain randomization	Increased robustness to domain shifts
[14]	A. RoyChowdhury et al.	Adapt object detectors to new domains without labels	Self-training approach	Enhanced adaptation in domain-shift scenarios

IV. CONCLUSION

This analysis examines breakthroughs in automated crater and boulder detection for planetary exploration, emphasizing the critical role of merging cutting-edge object detection and segmentation frameworks. The synergy of YOLOv8's rapid identification capabilities with SAM's granular segmentation accuracy has resolved persistent obstacles in planetary geology, such as distinguishing overlapping formations and handling multi-scale features. These hybrid systems have demonstrated superior performance compared to conventional YOLOv5-based approaches, delivering enhanced precision in feature mapping and versatility across diverse landscapes. Breakthroughs like anchor-free detection designs and zero-shot segmentation have boosted computational speed and model fidelity, validated using high-resolution lunar datasets from missions such as Chandrayaan-2. Such innovations simplify data analysis while minimizing human intervention, accelerating workflows vital for mission logistics and risk mitigation.

Persisting limitations include model generalization across extraterrestrial environments, necessitating expanded, heterogeneous datasets, and computational bottlenecks in real-time applications. Future directions should prioritize fusing multi-sensor data (e.g., spectral, thermal) and leveraging emerging paradigms like edge AI and compact neural architectures for onboard spacecraft systems. Implementing these strategies could transform exploration protocols, enabling scalable tools for terrain cartography, landing zone optimization, and surface dynamics research. With agencies preparing for lunar and Martian endeavors, such technological leaps will prove indispensable for mission success, scientific inquiry, and sustainable solar system exploration.

The review also investigates advances in AI-driven detection of plant nutrient deficiencies, highlighting transformative progress in automated diagnosis across agricultural systems. CNN-based models and their derivatives now dominate this domain, routinely exceeding 90% classification accuracy. Notable improvements include ensemble methods outperforming single-model frameworks and transfer learning techniques that broaden applicability. The transition from experimental prototypes to deployable tools has been propelled by mobile-integrated solutions and real-time monitoring platforms. Novel architectures like CAR-CapsNet and PND-Net have refined detection fidelity while optimizing resource efficiency. Enhanced preprocessing pipelines and multimodal data fusion further strengthen model robustness.

Challenges remain in dataset scarcity and model validation, alongside the complexity of distinguishing concurrent nutrient deficits. Subsequent research must prioritize real-time inference optimization, interpretable AI, and integration with precision agriculture ecosystems. The field is poised for expansion through edge computing, IoT networks, and advanced hyperspectral imaging, which promise to deliver holistic nutrient monitoring systems critical for sustainable farming and data-driven agronomy.

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