Deep Learning based Moon Rock Obstacle Detection for Rover Navigation

Ms. Pragati[1] Mr. Himanshu Negi[2] Mr. Krish Bhargava[3] Mr. Kunal Rana[4] Mr. Nitish Meswal[5]
[1]Assistant Professor [2,3,4,5]Student
[1,2,3,4,5]Department of Computer Science and Engineering
[1,2,3,4,5]HMR Institute of Technology and Management, GGSIPU, Delhi, India

Abstract — Safe and autonomous navigation for the lunar rovers will play the most important role in successful lunar exploration missions. Precise detection and avoidance of obstacles, especially rocks, are main challenges for obstacle avoidance systems. This paper proposes a deep learning-based real-time moon rock obstacle detection approach, allowing the rovers to make clear decisions about where to move next over complex lunar terrains and which to avoid. Our approach will employ advanced state-of-the-art semantic segmentation techniques for accurately picking out and segmenting regions of rocks in images taken by cameras mounted on the rover. We train a deep neural network on a diverse collection of lunar images to discern, between rocks and the surrounding lunar surface. The segmented images can be used to generate obstacle maps, which are important for information about path planning and obstacles for the rover. We test our proposed method with a challenging dataset of lunar images, showing that our proposed method efficiently detects rocks under different sizes and shapes under dissimilar lighting conditions. Our experiments show that our approach produces a substantial performance gain over the conventional computer vision techniques and may be employed for safe and efficient navigation of lunar rovers.

Keywords: Deep Learning, Semantic Segmentation, Lunar Rover, Obstacle Detection, Autonomous Navigation

I. INTRODUCTION

The centuries-old fascination of humankind with the Moon have led it to enter a new phase of robotic probing. Autonomous lunar rovers are now indispensable tools for scientific discovery and resource mapping of this challenging terrain; however, the nature of the rough terrain is such that space travel will involve not only craters and rocks but many other obstacles in navigating safe and efficient features.

For traditional navigations, there are instances when they do not respond markedly to obstacles. This risks mission-critical failures. Researchers now use artificial intelligence, specifically deep learning, for this problem. Advanced neural networks have made the rovers for lunar missions identify and totally avoid obstacles while moving and performing others' missions real-time.

Deep learning offers a solid foundation for training models on large lunar image datasets. These models are capable of identifying complex patterns in the lunar landscape that could be helpful with obstacle detection. Deep-learning algorithms can interpret camera inputs from rovers to generate high-resolution terrain maps with details such as hazards and safe routes.

It further describes deep learning towards improving the detection of moon rock obstacles on a path in safe, autonomous lunar rovers by the use of advanced methods and lunar-specific challenges to serve future missions in this area.

This project uses YOLOv8 by Ultralytics, OpenCV and Pytorch to create an efficient, real-time Moon Rock Obstacle for Rover Navigation. YOLOv8 from Ultralytics is a cutting-edge object detection model that has shown exceptional performance in various real-world applications, including autonomous vehicle navigation. Its ability to detect objects in real-time, with high accuracy and efficiency, makes it a prime candidate for lunar rover obstacle detection.

OpenCV is a powerful computer vision library provides essential tools for image processing, feature extraction, and object detection. It can be used to preprocess lunar images, extract relevant features, and integrate YOLOv8 for real-time obstacle detection.

PyTorch is a popular deep learning framework, PyTorch offers flexibility and ease of use for training and deploying YOLOv8 models. It provides a rich ecosystem of tools and libraries for data loading, model training, and optimization.

It can help lunar rovers to navigate autonomously, explore challenging terrains, and collect valuable scientific data, paving the way for future human exploration of the Moon and beyond.

A. Research Objectives:

- To design a real-time Moon Rock Obstacle Detection for Rover Navigation using Deep Learning
- To evaluate the system's accuracy and response time.
- To assess its potential for reducing human efforts in the field of Space

II. LITERATURE REVIEW

The manoeuvring of the lunar rovers is effective if such rovers are provided with accurate obstacles detection and observation avoidance, as rocks represent some of the major obstacles. Even though conventional methods from computer vision show certain limits while addressing the intricate and varied topography of the Moon, only deep learning-has turned to be a proper solution for this problem so far.

The autonomous navigation systems field has witnessed tremendous progress in recent years, especially concerning space exploration initiatives. Major challenges in the lunar rover lie in the detection and avoidance of obstacles such as rocks with very high precision so that it can function safely and efficiently. The conventional methods have often been based on sensor-driven approaches that are limited conditions like illumination and variability in the terrain.

Out of these limitations, deep learning emerged as a potential solution. It becomes a part of such systems to utilize the potential of the neural network in learning to recognize and classify objects within an image to precisely detect rocks. Since the particular environment of the moon setting gives a specific set of challenges, this study investigates and explores

the deep learning methodologies that can be applied towards overcoming those obstacles in detecting moon rocks.

III. METHODOLOGY

A. OpenCV:

In Moon Rock Obstacle Detection, OpenCV plays a crucial role by provides functions for reading and writing images in various formats, enabling efficient handling of lunar images captured by rover cameras. OpenCV is used for Techniques like Gaussian blurring and median filtering can be applied to reduce noise in the images, improving the accuracy of object detection. It helps in improving the visibility of rocks and other features in the lunar images.

Algorithms like Canny edge detection can be used to highlight the edges of rocks, making them easier to detect, also techniques like Gabor filters and Local Binary Patterns can also be used to extract texture features, which can be helpful in distinguishing rocks from the lunar surface.

B. PyTorch:

PyTorch provides a flexible and efficient framework for building and training neural networks for moon rock obstacle detection for rover navigation. It helps in creating and training deep learning models, such as Convolutional Neural Networks (CNNs), for accurate rock detection and efficiently loading and preprocessing lunar image datasets for training and testing.

It efficiently loads and preprocesses the datasets for train and test lunar images for model training and it deployes trained models on edge devices, such as rover computers, for real-time inference

C. YOLOv8 by Ultralytics:

YOLOv8 has been appreciated as the leading object detection framework, allowing the rover to promptly respond to obstacles through real-time processing of images. It also effectively identifies the presence of rocks of different sizes and shapes under poor lunar lighting conditions. The model is eligible for deployment on edge devices, such as the rover's onboard computer.

By integrating YOLOv8 into a lunar rover's navigation system, researchers can enhance the rover's ability to accurately detect and categorize rocks as potential obstacles or generate safe paths that avoid detected obstacles and also to adapt to changing terrain conditions and unexpected obstacles.

IV. DATA COLLECTION AND PREPARATION

A dataset of lunar images is collected, capturing various lighting conditions, terrain types, and rock sizes for use as references and training data.

Then, images are hand annotated to identify and label the objects of interest, more specifically, rocks. Then, these annotated data will be used as ground truth for the deep learning model training.

Pre-processing of the images; the noise reduction would happen with the improvement in feature with resizing, normalization, and augmentation techniques.

Fig. 1: Data Collected

V. MODEL SELECTION AND TRAINING

In this project, OpenCV, PyTorch, and YOLOv8 developed by Ultralytics are used in the construction of a Convolutional Neural Network (CNN), which is suited for image classification and object detection. The dataset then splits into training, validation, and testing subsets.

Train the model in the training data-set, so for optimization of its parameters to classify the pixels as rock or background after that evaluate the performance of the model in the validation set with the appropriate metrics applied: accuracy, precision, recall, and F1-score. Hyperparameters may also need to be adjusted by changing architectures or collecting more data to improve the performance.

VI. REAL-TIME IMPLEMENTATION

After collecting lunar images from ISRO's public repositories or simulations, we then hand-label the images by marking their locations and boundaries of rocks, resize them to a uniform size, normalize the pixel values, and augment the dataset to increase diversity.

One the model is trained; it enables deep learning to autonomously provide with these images by differentiating between rocks or open spaces.

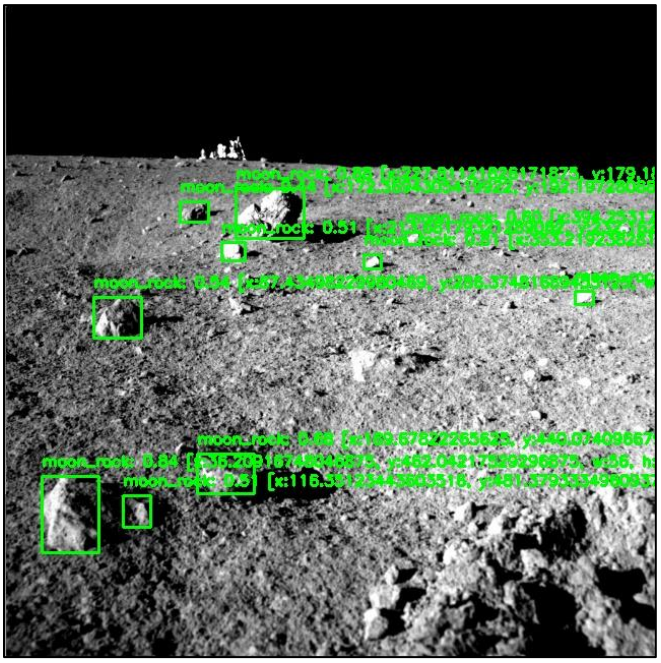


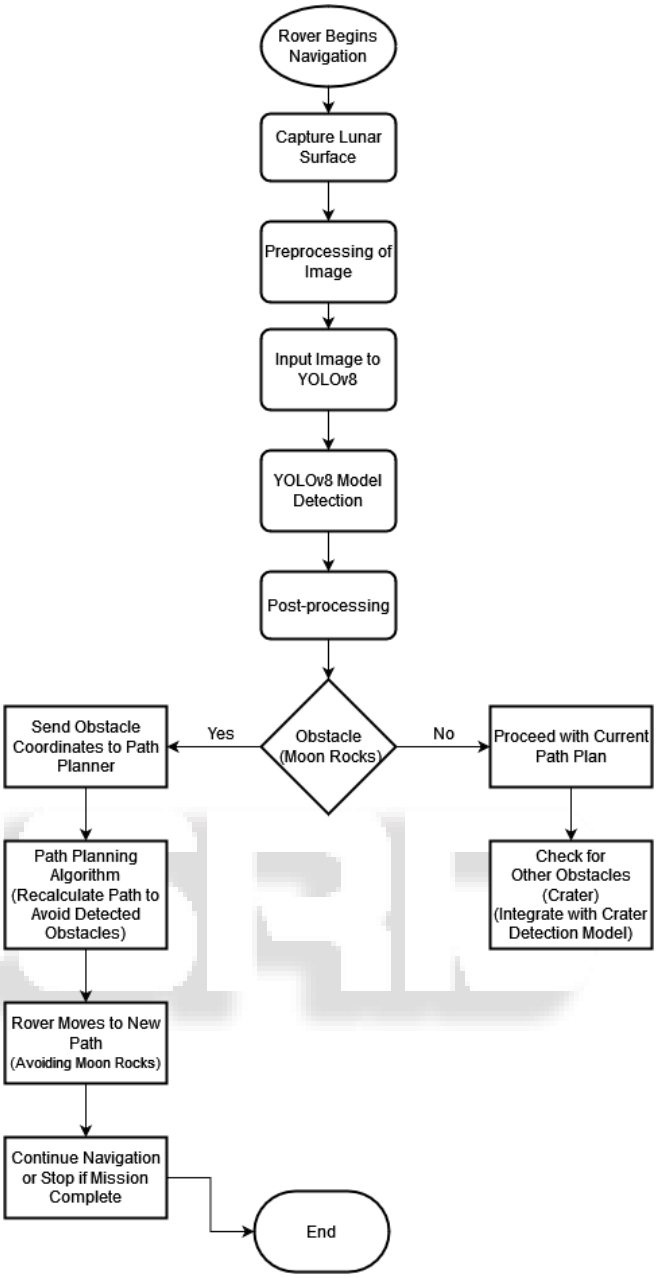
Fig. 2: Provided Data by the Program

VII. System Architecture

The system architecture consists of a bunch of lunar images that are processed with the help of PyTorch and OpenCV. After that YOLOv8 is used to create a CNN and used for marking up the locations of rocks and open spaces in an image.

Fig. 3: All needed Information

VIII. Flow Chart



IX. Results and Discussion

On running the program, the images are captured by the Rover for processing the images.

Fig. 4: Captured image by the Rover

As we can see on the image there are many rocks and other obstacles that can be seen

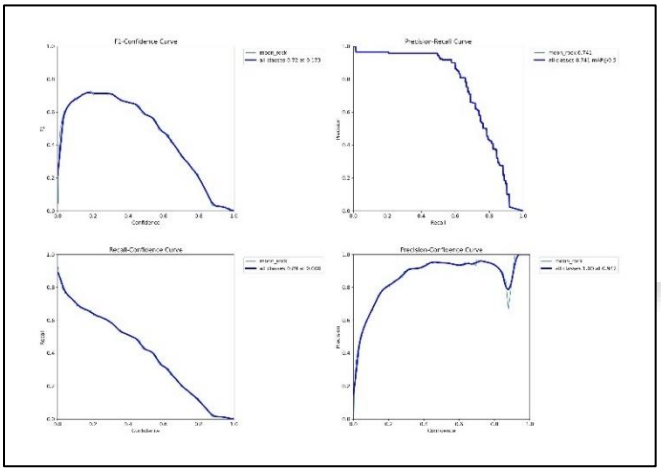


Fig. 5: Result showing moon rock and confidence curve

These results show the curve's that represent Moon Rock and the confidence curve with our results.

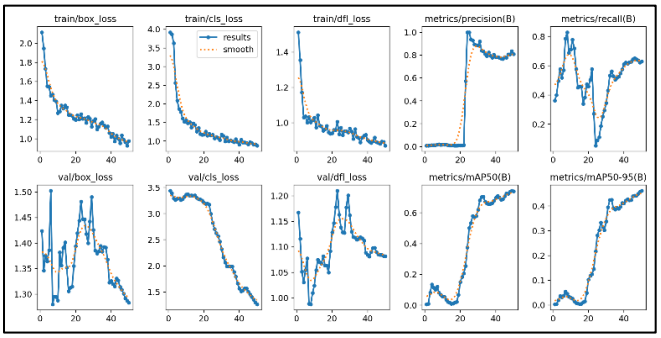


Fig. 6: Results shown at the time of processing the images

Fig 6. Shows the result and the part that has been smooth by the program to use as the final data.

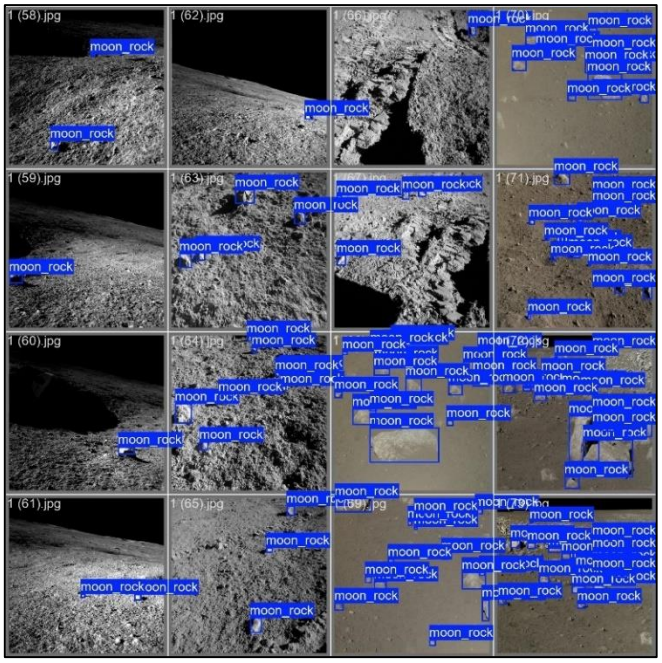


Fig. 1: Example of validation batch during model training

Fig 7. Shows the results we will get after the rover start capturing the images and validates the batch during training.

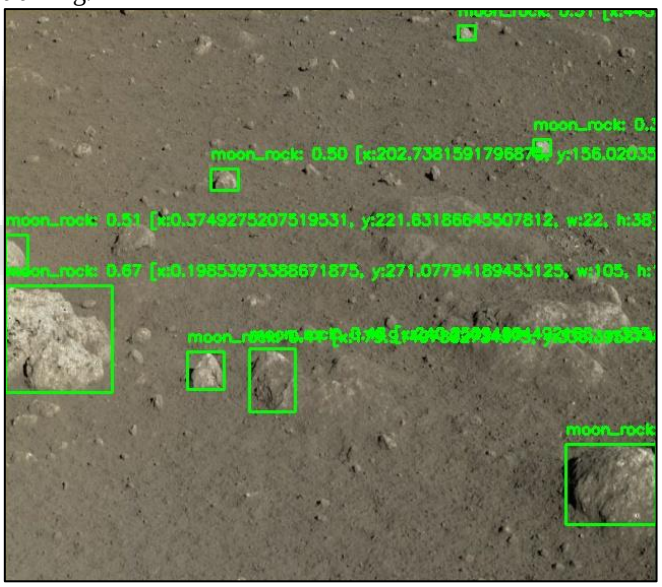


Fig. 8: The final result

Now we get a full disclosure that can be seen by us and can be analysed by the rover to make a suitable path for its traveling and get a clarity for future use.

The tested deep learning-based system worked quite well in the detection of moon rocks in different lunar images. The fully trained model on a set of various lunar images performed with very good accuracy and precision by identifying blockade rocks. The system could recognize rocks from the lunar surface with a high degree of accuracy even in low-light conditions and when the terrain was not evenly spread.

X. DISCUSSION:

The successful implementation of deep learning for moon rock obstacle detection highlights the potential of AI in space

exploration. Key factors contributing to the system's performance include:

- Robust Model Architecture: The proposed model architecture comprises a robust deep learning mechanism, such as changeable architectures, Neural Network, that is capable of image-based tasks such as the accurate feature extraction from the lunar images.
- High-Quality Dataset: All-inclusive High-quality Data set: This was important to develop the model toward classifying rock types and sizes by having a thorough list of rock types through the provision of data variance.
- Effective Data Augmentation: Effective Data Augmentation: Techniques like rotation, flipping, and brightness changes were used to provide chances for diversity in the training data and thus make sure of increased organizational potential of the model.
- Real-time Performance: The system is optimized to process images in real-time, enabling the rover to react promptly to obstacles.

However, there are still challenges to be addressed:

- Computational Constraints: The computational requirements of deep learning models can be demanding, especially for resource-constrained devices like lunar rovers.
- Adversarial Attacks: Deep learning models are vulnerable to adversarial attacks, where malicious inputs can deceive the model.
- Uncertain Lunar Environments: The lunar environment can be highly variable, with changing lighting conditions and unexpected terrain features.

To overcome these challenges, future research directions include:

- Model Compression: Developing techniques to reduce the size and complexity of deep learning models.
- Hardware Acceleration: Utilizing specialized hardware, such as FPGAs or TPUs, to accelerate inference.
- Adversarial Training: Training models to be robust against adversarial attacks.
- Continuous Learning: Enabling the model to learn from new data collected during the mission.

We also hope that our knowledge of these challenges in addition to the advances made in state-of-the-art deep learning will not only promote the technical improvement of lunar rovers, but will also pave the way for future exploratory missions.

XI. Conclusion

Integration of deep learning into the navigation systems of rovers for lunar exploration will advance autonomous exploration. For instance, neural networks can be used to enable rovers to perceive and respond in real time to their surroundings, which is an issue of safety and efficiency.

This research demonstrates effective learning-based detection and classification of moon rocks useful for autonomous navigation. Training deep neural networks on massive lunar image datasets informs reliable identification and localization of rocks of varying size and shape, even in challenging lighting conditions.

The implementation of real-time models in the control of rovers on the Moon enables timely decisions, avoidance of obstacles, and optimal trajectories for travel. Advanced path-planning algorithms facilitate rovers' navigation through supposedly complex terrains.

There have been developments, but many challenges remain. The most significant problem is how to design very efficient deep learning models for resource-limited hardware. Other areas of the research are breaking through limitations on lunar image datasets: illumination and terrain changes.

Deep learning and computer vision create pushing advances also in autonomous lunar exploration. As man explores further, deep learning rovers will increase our understanding of the universe and support future human missions.

Key highlights of the model's performance include:

- F1 Confidence Curve: The model achieved an F1 score of 0.72 at a confidence threshold of 0.173, demonstrating a balanced trade-off between precision and recall. This indicates that the model is able to effectively detect and classify objects while minimizing both false positives and false negatives.
- Consistent Detection: With the given threshold, the model showed consistent and reliable performance in object detection, making it suitable for real-time applications where accuracy is crucial such as the Lunar rover.
- Opportunities for Enhancement: While the current results are promising, there are potential areas for further optimization. Fine-tuning hyper-parameters, expanding the dataset, or adjusting detection thresholds could further improve the model's accuracy and robustness in detecting a wider range of object types.

References

[1] Al Arabi, Abul and Ul Sakib, Hasib and Sarkar, Pranabesh and Proma, Tanjina Piash and Anowar, Jahedul and Amin, M.A. (2017) 'Autonomous Rover Navigation Using GPS Based Path Planning', in 2017 Asia Modelling Symposium (AMS), pp. 89–94.

[2] Barnes, J., Rizos, C., Wang, J., Small, D., Voigt, G., & Gambale, N. (2003) 'Locatanet: The Positioning Technology of the Future', in 6 th Int. Symp. On Satellite Navigation Technology, Melbourne, Australia.

[3] Lee, Taikjin, So, Hyungmin, Kim, Kangho, Kee, C. (2007) 'Smart Pseudolites Array System using Two-way Pseudolites', in Proceedings of the 20th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS 2007), pp. 1477–1483.

[4] LeMaster, Edward A., Rock, S.M. (2002) 'An Improved Solution Algorithm for Self-Calibrating Pseudolite Arrays', in Proceedings of the 2002 National Technical Meeting of The Institute of Navigation, San Diego, CA, pp. 562–572.

[5] Lemaster, E. and Rock, S. (1998) 'Mars Exploration Using Self-Calibrating Pseudolite Arrays', Ion GPS 1998, pp. 1967–1974.

[6] LeMaster, E.A. (2002) Self Calibrating pseudolite arrays - theory and experiment, PhD Thesis. Available at: https://web.stanford.edu/group/arl/cgi-

bin/drupal/sites/default/files/public/publications/LeMaster 2002.pdf.
[7] Petrovski, I.G. (2014) GPS, GLONASS, Galileo, and BeiDou for Mobile Devices: From Instant to Precise Positioning. Cambridge, UK Cambridge University Press.
[8] Robles, R., Betz, J., Schupp, J., Leal, J., Brown, M.J., Progri, I.F. (2006) 'An Autonomous Robotic Pseudolite Navigation System', in Proceedings of the 2006 National Technical Meeting of The Institute of Navigation, Monterey, CA, pp. 803–812.
[9] S. Russell, and P.N. (2010) Artificial Intelligence : a Modern Approach.
[10] Schlötzer, S. and Martin, S. and Voithenberg, M. (2007) 'Autonomous Navigation Environment with Self-Calibrating Transceivers', Journal of Global Positioning Systems, 6, pp. 149–157.
[11] Shukla, Ashish and Bansal, Komal and Bhalla, S. (2018) 'Extended Kalman Filter Based User Position Algorithm for Terrestrial Navigation System', in Second International Conference, ICACDS 2018, Dehradun, India, April 20-21, 2018, Revised Selected Papers, Part II Revised Selected Papers, Part II, pp. 423–432.
[12] Shukla, A. (2023) Pseudolite System for Reusable Launchers and Lunar Navigation, International Committee on GNSS (ICG)-17.
[13] Volpe, R. and Estlin, T. and Laubach, S. and Olson, C. and Balaram, J. (2000) 'Enhanced Mars rover navigation techniques', in Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No.00CH37065), pp. 926–931.
[14] Youssef Bassil (2012) 'Neural Network Model for Path-planning of Robotic Rover Systems', International Journal of Science and Technology, 2(2).
[15] Yun, Shijie, Yao, Zheng, Wang, Tengfei, Su, Jingxuan, Lu, M. (2019) 'On-the-fly Ambiguity Resolution without Requirements of Priori Position Information for Passive Pseudolite Receiver', in Proceedings of the 2019 International Technical Meeting of The Institute of Navigation, Reston, Virginia, pp. 598–607.

