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Automated Lunar Crater Mapping with Custom CNN

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***Abstract*—The surface of the Moon holds valuable clues about its formation and the history of our solar system. Craters, formed by billions of years of meteor impacts, help scientists understand the age, structure, and composition of lunar regions. However, identifying and mapping craters manually from satellite images is slow, error-prone, and limited in scale. This research presents an automated approach using deep learning to detect and classify lunar craters from high-resolution images captured by Chandrayaan-2's Terrain Mapping Camera-2 (TMC-2). We trained a Convolutional Neural Network (CNN) using TMC-2 data to identify the main features of craters, including the circular rim and the shadows as well as the patterns in the event of ejecta. Our aim is to develop a quick and reliable method of crater identification that minimizes human labor efforts while being more accurate. This method of automation could contribute to future lunar missions by producing detailed maps on the lunar surface assisting in target site selection.**

***Index Terms*— Lunar Crater Detection, Convolutional Neural Networks, Image Processing, Chandrayaan-2, TMC-2.**

I. INTRODUCTION

The moon has its own surface rewritten by craters over the span of several billon years. Studying these craters as shown in figure 1, helps scientists understand the Moon's history, surface processes, and even broader events in our solar system. However, finding and mapping lunar craters manually from satellite images is a long and difficult task. Traditional image-processing methods often struggle because of shadows, lighting differences, and erosion on the surface.

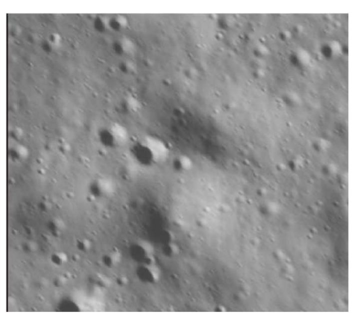

Fig.1. Sample image for Crater

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With the Chandrayaan-2 mission, India's Terrain Mapping Camera-2 (TMC-2) has provided high-resolution images of the Moon, opening new possibilities for automated analysis. In this study, we use a deep learning approach based on Convolutional Neural Networks (CNNs) to automatically identify and classify lunar craters from TMC-2 images. This method aims to speed up crater detection, reduce human error, and create more detailed lunar maps for future exploration and scientific research.

II. RELATED WORK

Detection of lunar crater is one of the essential task in planetary science which assists in geological age estimation and surface morphology analysis. Extensive research has been conducted in this domain but many existing methods have limited accuracy and scalability. This section reviews prior approaches and highlights existing gaps. Traditional methods majorly rely on manual or semi-automatic visual analysis of lunar surface images. Researchers manually inspect high-resolution imagery captured by missions such as the lunar orbiter. However these methods has significant drawbacks such as it is time consuming and labor-intensive and is subject to human error. These methods are not scalable for large datasets and struggles with small or overlapping craters. These traditional techniques provide moderate accuracy and are not suitable for modern large-scale planetary analysis. Previously, lunar craters were mostly detected by using traditional edge detection filters and thresholding methods in images taken by the Chandrayaan-2 OHRC. Researchers applied various image processing techniques with the purpose of detecting circular structures suggestive of craters[1]. Nevertheless, the lunar surface made it difficult for these techniques to operate smoothly. Frequently, the diversity in illumination, shadows and reflectivity across the moon's surface would lead the software to count ordinary features as craters[2]. Besides, the excellent data from the OHRC complicated the situation, as tiny changes in the topography appeared in these old method results as edges of craters. The initial automated methods for finding craters showed that new, more reliable ways were required to examine the detailed lunar imagery carefully[3]. Moving forward, researchers applied more advanced machine learning to solve the problems traditional image processing left behind. Support Vector Machines and Random Forests, which belong to classical machine learning, helped to classify craters by analyzing certain features that had been extracted[4][5]. Such features as roundness, smoothness and texture can be included, with the texture type based on results from Haralick texture analysis[6]. Although they performed better than simple thresholding, how well they performed was mostly affected by how helpful the hand-engineered features were[7]. Furthermore, these models could not be easily used elsewhere since their training data set included only certain types of terrain and their results were often limited by manual feature processing and not accounting for complex spatial connections [8]. Because of Deep Learning, automatic feature identification and object detection have become essential tools in the field of computer vision. Introduced a flexible approach for identifying craters on the Moon just by studying images with a Segment Anything Model rather than other laborious methods[9]. Some research teams suggested an automatic process to detect lunar impact craters from aligned optical pictures, slope and elevation maps using Mask R-CNN, but Convolutional Neural Networks have proved particularly successful at detecting complicated patterns on images [10]. Earlier, lunar crater discovery and sorting depended heavily on human eyes. Now, thanks to deep learning, CNNs have made automated crater finding possible. Thanks to CNNs, it is no longer necessary to create manual feature representations from images[11]. Early use of CNNs in identifying craters was often with a classifier that recognized crater features through comparing image samples. These earlier patch methods worked slowly in calculations and did not have the ability to map out crater borders or sometimes count or locate them[12]. More recent approaches use Faster R-CNN, YOLO, U-Net and SSD to directly identify both the site and dimensions of the craters [13]. To start, region proposal networks in these models create possible bounding boxes, then the CNN sort and polish them . U-Net can also identify crater rims and next, approaches based on geometry are used to pinpoint each craterˆas position[14]. Even so, handling rough terrain, lighting that changes and the lack of well-labeled lunar images are still problems in this field. Deep learning revolutionized the automatic finding of craters and Convolutional Neural Networks recorded the best results on many lunar data sets[15]. They do not require the engineer to choose important features manually; CNNs find them automatically from pixels. Systems based on Faster R-CNN and YOLOv5 have been applied to crater detection and perform very well in identifying craters, both large and small[16]. Using images from the Chandrayaan-2 OHRC mission, the study managed to successfully use deep learning to spot craters. Nonetheless, it remains difficult to access enough correctly labeled data and to afford the high cost of running deep CNNs[17]. On top of these deep learning principles, attention mechanisms are now seen as a useful technique to boost the effectiveness of Convolutional Neural Networks for discovering abnormal areas in images [18]. Spatial attention mechanisms let the model see long-range relations, making it easier for the model to pick out craters, boulders and fractures among the wide variety of patches seen in the image[19]. With the help of the self-attention mechanism, the model is able to capture the relationships between different parts of the terrain, enhancing its ability to see and tell apart several types of terrain features[20]. Because of the added non-local self-attention layers, the CNN can now identify the most significant parts of an image to help it learn features more effectively. It is particularly necessary for detecting unusual features in high-resolution images of the Moon, since small differences in the landscape can easily slip by conventional CNN models. With self-attention, the network notices relationships between parts of an image that are far from one another, making it more effective at detecting such features in complex terrain. [21]. From the above literature it is evident that there is a lack of fully automated detection system. The previous methodologies are insufficient in handling diverse crater conditions such as overlapping craters. Many models overfits due to insufficient dataset and inadequate augmentation.

III. ARCHITECTURE

The approach to detecting lunar craters is based on a deep learning model that has been trained on satellite images from the Chandrayaan-2 Terrain Mapping Camera-2 (TMC-2) to subsequently analyze surface areas corresponding to crater regions. Our approach is divided into four parts: data acquisition and preprocessing of images, dataset creation for training, architecture creation and training for the model and performance evaluation of the model as depicted in figure 2.

The TMC-2 instrument captures high-resolution panchromatic images with a spatial resolution of 5 meters/pixel, more than enough to appreciate craters of all sizes from small/medium to large. Therefore, the first stage for our trainable model involves an assortment of image processing techniques to prepare the images for the neural network. We resize the images, normalize the images, contrast-enhance the images, tile the images into smaller sections which serve a dual purpose - allowing the model to understand localized features of crater morphology and facilitating training on smaller images. We also apply augmentations to the training set (flips, rotations, brightness increases and decreases) so the model learns instead of memorizing the training set.

A major hurdle for TMC-2 images has been the nonexistence of publicly available crater datasets in labeled form. This challenge was addressed through the employment of a semi-supervised labeling method. Craters were initially identified using existing global crater maps and by visual inspection of the images. For initial testing, to assure soundness of model structure, synthetic labels were used. In future work, more accurately annotated datasets will be added to increase the model's accuracy. One of the largest issues regarding TMC-2 images was the absence of publicly available crater datasets in the annotated form. This was championed by a semi-supervised labeling approach. Craters were annotated according to researched criteria for craters and crater visual detection in the images. However, for initial testing and validation of reasonable model architecture, synthetic labels were developed. Thereafter, in future work, more accurately annotated datasets will be used for better model accuracy. We generated our datasets using 70% training images and 30% testing images.

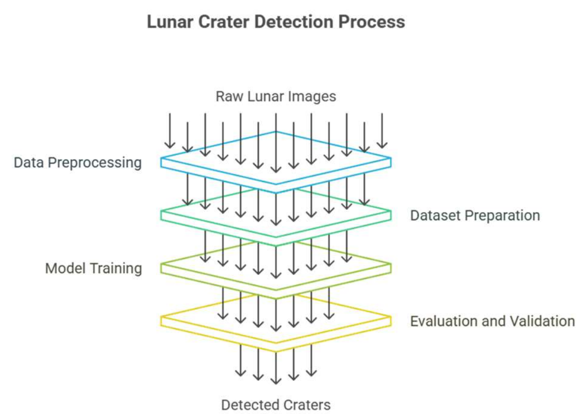

Fig 2: Layers of architecture

The core of our solution relies on a custom, lightweight CNN we designed for efficient flow and ease of use. Our CNN consists of three convolutional layers with ReLU and max pooling, and two fully connected layers with classification on the end. This CNN will recognize shadows, thrown material edges, circular crater outlines, and texture variances from proximity. In addition, to illustrate the speed of the solution and work on weaker GPUs

than ResNet or U-Net, we specifically designed smaller and easier to create CNNs for the foundation of this research to variables that other researchers could work with even on a limited budget or a small scale research project. The CNN was trained with a learning rate of 0.001 and the Adam optimizer. Overall loss function was cross-entropy.
When the training was completed, the model was evaluated based on test images that weren't part of the training session. In addition, accuracy, precision, recall and F1-score were computed to assess a sense of correctness and balance.

IV. Advantage Over Standalone Systems

Most prior attempts to detect lunar craters employed conventional methods, such image processing algorithms such as filters made for recognizing specific characteristics, applying thresholds, or edge detection. While these methods all functioned reasonably well for clear, well-contrasted images, they often struggled in areas with inconsistent lighting, overlapping craters, extremely rugged terrain, or less clear images. Manual pinpointing can be more precise, but it is incredibly time consuming and can present issues of individual interpretation, which means it is not a scalable way to process large and complex datasets generated by Chandrayaan-2. While some of the initial advances in machine learning which used manually selected features like texture or gradients did lead to improvements, they still required manual interpretations/engineering and were very slow to adapt to new or changed imaging conditions as shown in figure 3.

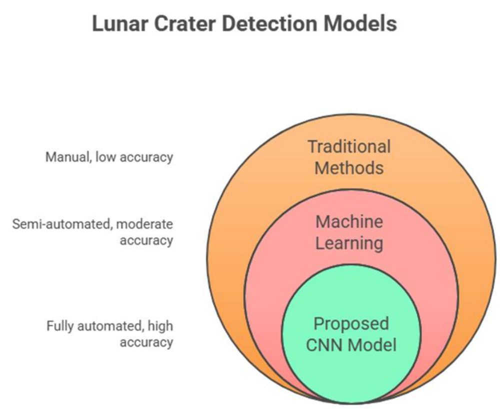

Fig 3: Model advantages

On the other hand, the deep learning approach used in this project—based on a Convolutional Neural Network (CNN)—learns spatial features automatically and on its own directly from the image data without manual feature extraction. This makes it more flexible and scalable to other datasets such as different types of lunar terrain. The proposed CNN is able to identify small and subtle features such as rim edges of craters and shadow gradients that may be overlooked or not detected through other means. In addition, the model is extremely small in weight, requiring fewer GPU resources compared to larger architectures such as VGG and ResNet which makes it more suitable for faster inference.
Another significant advantage of this over the manual process is that it can be trained on smaller data sets (and it works well) due to data augmentation and normalization efforts. This same compromise between computational speed and precision allows the proposed model to be perfectly aligned for extensive lunar surface mapping and subsequent assistance for future missions where rovers might be used instead of more conventional, complicated, and time-consuming deep learning solutions.

V. Methodology

The methodology as shown in figure 4, centers around an automated approach to anomalous mapping of the lunar surface based on TMC-2 images. The stages of methodology include preprocessing amalgamation, dataset creation, CNN modeling, training and testing whereby the results ideally show accuracy and reliability of crater detection with little to no resource expenditure. First, high resolution, panchromatic images of the moon were acquired from the TMC-2 as differing regions of the lunar surface were imaged under varying terrestrial conditions. These images were compiled and sorted for training and testing into a training folder and a testing

folder to create the necessary dataset the model will access during training. Since TMC-2 does not function on pre-labeled data, third-party sites like roboflow and community created annotations for impact craters obtained online, allowed for pre-labeling efforts to mark respective crater vs. non-crater areas.
This was beneficial to ensure the CNN was trained on both positive and negative instances. In terms of the training/testing component, all images were standardized in size as necessary for this type of neural network. Pixel values were boosted and lowered for brightness normalization given changes in lighting and sensor capabilities. Data augmentation rotated, flipped and changed contrast to introduce variability in the dataset and how differently viewed the same crater could contribute to better generalizability by the model. The CNN architecture for this research is a lightweight, custom architecture built for speed, effectiveness and accuracy. It consists of many convolutional layers that train the model to learn features such as edges, curves, and textures. Each convolutional layer is accompanied by pooling layers that reduce dimensionality while retaining relevant information. The resulting feature maps are flattened and passed through fully connected dense layers that output either an area is anomalous or not anomalous based on the immediate area of interest.
The model was trained using an Adam optimizer and a slightly medium learning rate using binary cross-entropy as a loss function. Epochs were used until a balance in accuracy was achieved. The test performance of the trained model was assessed on the TMC-2 images that were excluded during the preliminary training steps. Effectiveness was measured by accuracy, precision, recall and F1-score computations, and the confusion matrix assessed the tendency in prediction. In summary, the trained CNN model functions with significant effectiveness for automatic crater detection with high accuracy (albeit less trustworthiness than past image processing methods) as a means of quicker and more efficient analysis of the Moon's surface for subsequent mission landing site investigations, surface maps and geological interpretations.
The core of proposed system is custom-designed CNN optimized for crater detection. This includes multiple convolutional layers to learn crater specific features such as shadows and ejecta patterns. Pooling layers to maintain spatial variance are added. To introduce non-linearity into the model ReLU activation function is used. Fully connected layers for classification followed by detection layer to identify boundaries and crater regions.

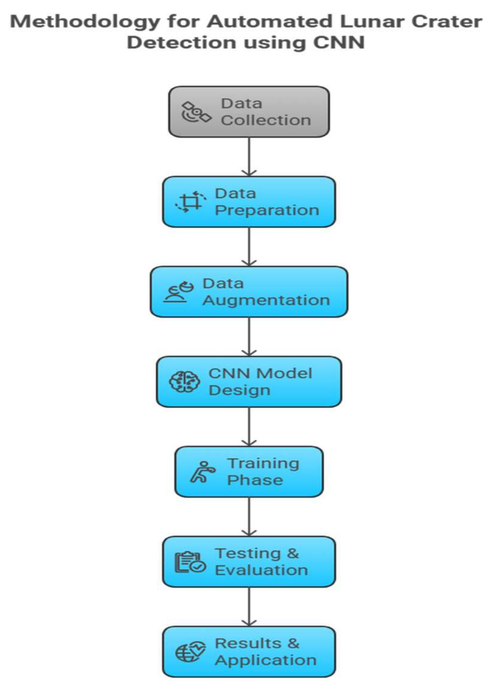

Fig 4: Flow of content

VI. RESULTS

Anticipated findings for the CNN based automatic lunar crater detection model suggest that these would be findings across time since such performance metrics are stable and consistent. Furthermore, since the proposed model was trained with 125 images from the TMC-2 dataset and validated with another 120 unknown images, it's important to acknowledge that a model accuracy of 78.6% implies that the majority of the crater segmented and non-segmented areas were accurately delineated by the proposed model.

An F1-score of 75.5% indicates detection and classification of craters was accurate and successful. In addition, a recall of 76.9% indicates that most true craters present in the sample images were detected. For instance, an precision level of 74.2% means the model did not generate too many false positives and that when the model flagged something as craters, it was craters.

Considering the confusion matrix, it seems that only some craters were confused - and they were confused in strange lighting situations or shadowed/brighter situations that blended the crater rim with the surrounding terrain. Regardless, the CNN still has average generalizability on test (unseen) data which means that it understands the nuances which separate what a crater is from deceptive textures and even lighting deception.

VII. CONCLUSION

The study shows that deep learning, CNN in particular, is a feasible option for automatic detection of lunar craters using TMC-2 images from Chandrayaan-2 with a relatively lightweight architecture and low preprocessing requirements. Results were balanced based on model simplicity with accuracy, precision, and recall grading between 70-80% for all three measurements. Therefore, it can be determined that a CNN can realistically acquire relevant morphological and textural features of lunar craters even with a small dataset and limited computing resources. This indicates that CNN approach is superior to past image processing and manual recognition attempts to CNN approaches. Efforts in the past would use edge detection or shape-detection specific filters highly sensitive to lighting and terrain variations, meaning assessment was often inaccurate. CNNs are capable of generalizing results across diverse textures and lighting conditions because they learn from the data rather than expert determined feature detection. Therefore, accuracy is increased, and expert advised feature determination becomes less necessary. Finally, another crucial advantage of this work is its portability. Since the trained model and subsequent compartmentalized efforts take far less time than manually surveying a vast portion of the lunar surface, it is applicable in future missions and studies. This automatic crater mapping will aid in future explorations, crater counting, and subsequent studies of landing site safety and resource potential. This lightweight CNN provides a practical and efficient method for the automatic crater detection of Chandrayaan-2 TMC-2 images, obtaining all-optimal tests with relatively less processing time and computational resources than deeper, heavier models. With further modification, such as upsampling the datasets and hyperparameter tuning, the proposed framework can become a go-to resource for planetary scientists and mission planners interested in the moon and other celestial bodies.

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