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Automated Lunar Crater Detection using YOLOv8 on Chandrayaan-2 Imagery

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Abstract

Craters are one of the most noticeable structures on planetary surfaces, which are utilized for spacecraft navigation, hazard identification, and age calculation. A number of factors make crater detection a difficult job, including complicated crater characteristics, variable sizes and forms of the craters, planetary data types, and data resolution. An innovative method for identifying and examining craters on the lunar surface using the remote sensing images from Chandrayaan-2 and employing deep learning techniques is proposed in this research. By making use of the extensive dataset from Chandrayaan-2, the proposed approach, YOLOv8-CCNet, uses convolutional neural networks (CNNs) and YOLOv8 to automatically detect crater features with great accuracy and efficiency. The proposed approach of using modified YOLOv8-CCNET showed an accuracy of 90% and IoU of 0.75. By combining remote sensing data processing with deep learning, the study aims to improve the precision of crater detection and characterization. This analysis helps classify different geological areas on the Moon. The techniques developed in this research not only increase the understanding of the Moon but could also be applied to studying other planets, contributing significantly to the field of planetary science.

Keywords: YOLO, Convolutional Neural Networks, Image Processing, Crater Detection, Remote Sensing.

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1. Introduction

Remote sensing has revolutionized crater detection on celestial bodies like the Moon, providing a non-invasive means to study their morphology and distribution. By analyzing statistics obtained from orbiting spacecraft such as Chandrayaan-2, remote sensing strategies discover and characterize craters based on awesome spectral signatures and surface topography. Utilizing advanced algorithms and multispectral imaging, this technique allows the automated detection of craters throughout extensive lunar terrains [1]. Finding lunar craters is essential for scientific research, navigation, and terrain assessment during lunar exploration missions. Conventional methods for locating craters depend on semi-automated techniques or labor and time-intensive hand inspection. Deep learning algorithms provide a precise and efficient means of automating this process [2].

Understanding the distribution of craters in terms of their location and size is essential for studying the objects that collide with planets and how such collisions have shaped the solar system. By analyzing this data, scientists can estimate the frequency of impacts across the entire solar system [3]. Researchers also examine impact craters to learn more about various factors that affect their appearance, including the amount of energy involved in an impact, the angle at which the object strikes the surface, the properties of the material making up the planet's top layer, the size and type of the object causing the impact, other factors like the strength of materials and gravity [4]. This knowledge has many practical applications, such as helping spacecraft navigate through space or selecting suitable landing sites for future missions. Crater analysis plays an important role in choosing landing sites for exploration missions. It helps in finding safe and scientifically valuable spots for both robotic and human exploration efforts [5]. By studying craters, it is possible to gain insights into the geological processes of celestial bodies and use this knowledge to plan future exploration missions. Crater detection poses numerous challenges because of the complex nature of planetary surfaces and imaging conditions [6]. One massive problem is the presence of diverse terrain capabilities that make it difficult to understand or mimic crater signatures, including shadows, boulders, and geological formations [7]. Additionally, versions in lighting fixtures situations, surface texture, and image decision can introduce noise and artifacts, making it tough to differentiate craters from background clutter [8]. Moreover, the abnormal form and numerous morphologies of craters complicate their identity and classification, requiring sophisticated algorithms capable of spotting diverse crater kinds [9]. Overcoming those challenges in crater detection is essential for advancing the information of planetary surfaces and supporting destiny exploration missions.

As per the study by [10], You Only Look Once (YOLO) is one of the most widely used algorithms for object detection. It uses the context to its advantage and predicts objects based on the global information in an image. It also does detecting small, multi-scale items. In this study, a modified YOLOv8 is proposed with the aim of identifying lunar craters. As mentioned in [11], data collection, annotation, model training, and inference are the steps in the YOLOv8 process that lead to reliable, highly accurate, and scalable crater detection. The author's [12] states that the most prominent geomorphic structural features on the surfaces of the planets are craters. In addition to being clear indicators of the physical features of the lunar surface, their traits, like morphological and spatial distribution, play a significant role in establishing surface chronologies and providing further context for understanding the lunar development.

The main objective of this research is to develop an automated system to detect and analyze craters in Chandrayaan 2 lunar surface images. With the help of computer vision and machine learning, craters were accurately identified while minimizing false detections. By extracting meaningful crater features, the system provides insights into lunar terrain complexities, facilitating scientific investigation and advancing our understanding of the lunar landscape and its geological evolution.

2. Related Work

Recent advancements in lunar crater detection encompass various approaches. YOLOv8, a deep learning model, performs better in terms of speed and accuracy, automating crater identification through image analysis. Its efficiency lies in processing vast datasets swiftly, aiding planetary exploration. Complementing this, the Hough Transform detects craters by recognizing circular shapes, optimizing edge detection for precise results. Anchor-free deep learning, as explored in CenterNet, provides another method by focusing on crater center point detection and size regression, achieving high recall and precision. Additionally, models like YOLO-Crater customize YOLO architecture for lunar and Martian crater detection, showcasing strong performance and generalizability. These diverse methods highlight ongoing efforts to enhance automated lunar crater detection, important for planetary research and exploration.

For small-scale crater detection, [4] introduces an automatic method using anchor free deep learning. This method effectively detects various types of impact craters, including dispersal and connective ones. Another approach for small crater detection is YOLO-Crater model that is used to detect small craters on the Moon and Mars [6]. This model addresses the crater sample imbalance problem by replacing the VariFocal and EIoU loss functions and incorporating a CBAM attention mechanism to reduce interference. Their outputs showed that the data type and visualization augmenting techniques significantly influence detection accuracy, with the DOM-data type and CE-2 DOM-MMS method yielding the best results. The Lunar YOLO-Crater outperforms YOLOX in both regions, with F1 scores of 74.66% and 76.11%, respectively.

Table 1. Summary of Literature Review

Author(s)	Study Focus	Methods / Models Used	Key Findings
S. Zhang et al [4]	Deep Learning based impact crater detection	CenterNet model without anchors and transfer learning	Recall of 73.66% and precision of 78.27%
Nour Aburaed et al [5]	Yolov5, Yolov6, mAP, mAR	SGD /Adam / AdamW	AdamW optimizer outperforms SGD and Adam
L. Mu et al [10]	Model for Small Crater Detection	VariFocal and EIoU losses, the CBAM attention mechanism, and DOM-MMS	It was discovered that the ideal stretching technique was CE-2 DOM-MMS (Max-Min Stretching).
Atal Tewari et al [13]	Difficulties in crater recognition because of the craters' difficult characteristics	Semantic segmentation, object detection, and classification.	Analyse each architecture's crater-detecting efficacy and possible uses.
Yaqiong Wang, Xiaohua Tong[14]	CDA using a random projection depth function and a conventional texture feature	CDA, Candidate Craters Detection, random projection depth function	Competent in locating craters on multiple scales, particularly small-scale craters.
Chen Yang, Chunali Li, Bin	Automated age determination and	DL, ML, CNN(ResNet101)	Two-phase crater detection method to

Lui [18]	crater identification		extract a significant amount of semantic data
Vashi Chaudhary, Digvijaysinh Mane [19]	Bounding box-based object detection.	CNN-Based Feature Extraction using Relu activation	YOLO can be used for database creation and crater counting
Riccardo La Grassa, Gabriele Cremonese [20]	Super-resolution-based impact crater detection	YOLOLens(Generator and YOLOv5), ADAM optimizer	SR enhances the object detection capability, in terms of in terms of Precision, Recall, and mAP

The study discusses the difficulties of crater detection due to the intricate properties of craters and surveys deep learning crater detection algorithms by classifying them into three parts [13]. This research examines the evolution of these automatic crater detection algorithms and re-implements semantic segmentation-based crater detection algorithms on a standard dataset to evaluate their accuracy and speed. It also identifies several open issues and suggests promising future directions for improving crater detection approaches. To compare the efficiency of YOLOv5 and YOLOv6 in crater detection, the researchers conducted an experimental review using Martian/Lunar Crater Detection Dataset and various optimization functions-SGD, Adam, and AdamW [15]. Although YOLOv6 is generally considered an advanced version of YOLOv5 and AdamW is thought to outperform other optimizers, their experiments show inconsistent outcomes [16-17]. In some cases, YOLOv5 outperforms YOLOv6 with each optimization function excelling under dissimilar conditions [18]. Similarly, there have been many previous researchs and studies for crater detection, including image processing [22], machine learning [23][24], and deep learning models [25-28]. Table 1 presents a summary of the literature review. This research proposes the use of a modified YOLOv8, YOLOv8-CCNET, for carter detection and analysis.

The main contributions of this research are:

- Development of a high-resolution lunar surface image dataset specifically from the Chandrayaan-2, consisting of 1400 images of 512x512 pixels and focusing on the south pole region of the Moon.

- YOLOv8 was modified with a backbone optimized for spherical features to accurately detect craters in lunar image segments. The improved YOLOv8 model achieved an accuracy of 90%, as seen in the Experimental result.
- The proposed model is an effective and scalable system for detecting craters on the southern pole region of the Moon in real time.

3. Proposed Work

In this research, a modified Yolov8 algorithm called YOLOv8-CCNet (YOLOv8 with CNN for Chandrayaan-2) is proposed for better detection of craters on the lunar surface. YOLOv8 was modified with a backbone optimized for spherical features to accurately detect craters in lunar image segments. A custom CNN with circular filters was used in the early layers for this purpose. Most CNNs use square convolutional filters (e.g., 3×3, 5×5), which are good at detecting lines, edges, and corners, but not necessarily ideal for shapes like circles or ellipses, which are central to crater detection. The circular filters helped in detecting crater rims early in the network, reducing false positives from non-circular depressions, and increasing generalization across differently sized craters. Figure 1 shows details of the workflow of this study.

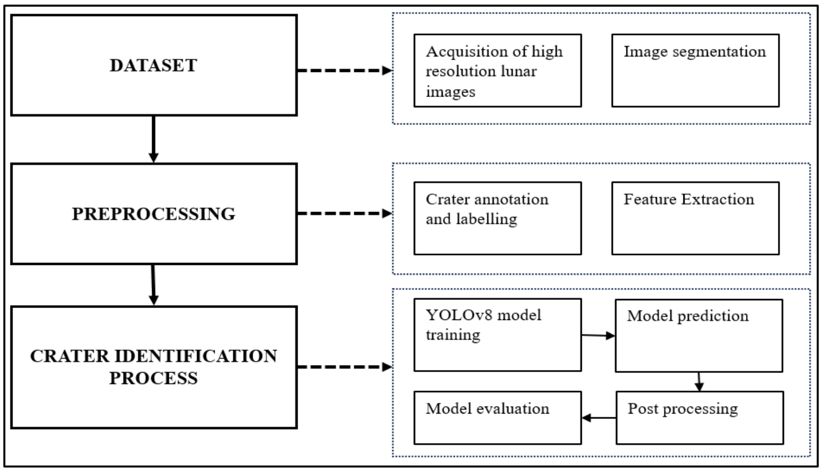

Figure 1. Block Diagram of the Process.

3.1 Data Acquisition

High-resolution lunar surface images of the Moon's south pole region, acquired by the Chandrayaan-2 mission, were downloaded from ISRO’s website [29]. Ensuring a comprehensive coverage of this specific area is essential as the South Pole region holds significant scientific interest. By obtaining images specifically from this region, the analysis can focus on exploring and understanding the characteristics of the lunar surface in the south pole area, contributing to the knowledge of lunar geology and aiding in the detection and analysis of craters in this particular region. As shown in Figure 2, different instrument footprints were used for detecting different craters with respective swath and spatial resolution. The 4 payloads used were IIRS (Imaging Infrared Spectrometer), OHRC (Orbiter High Resolution Camera), DFSAR (Dual Frequency Synthetic Aperture Radar), and TMC (Terrain Mapping Camera).

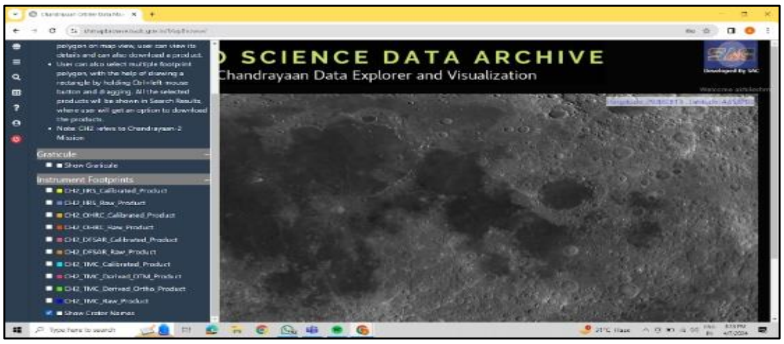

Figure 2. Ch-2 Tool used to get the Images of the Moon.

Different steps required to get craters in specific locations as shown in Figure 3. Initially, the instrument was selected, then the PDS Product and the area of interest, which includes the latitude and longitude of the required location. Optional steps include the observation date range or searching by the PDS Product ID.

Figure 3. Options to Select the Instrument, Product Type, Area of Interest

3.2 Crater Annotation and Labeling

In order to properly train a machine learning model, it had to be provided with a precise definition of what constitutes a crater in the lunar landscape. For this, manual locating and labelling every crater in the images was processed using LabelImg tool. This involved labelling each identified crater and drawing precise bounding boxes around them. All bounding boxes were assigned the label "Crater" to create a single-class dataset suitable for the YOLOv8-CCNet.

The ground truth dataset was created by a careful annotation process using LabelImg. The green coloured bounding boxes as shown in Figure 4 are used to label the craters. The craters in each segmented image were manually annotated using the LabelImg tool. Bounding boxes were drawn around each crater, ensuring accurate delineation. In the annotation process, bounding boxes were constructed around every crater, which gave the model a "teaching signal." This signal helped the model learn the patterns and characteristics that distinguish craters from the surrounding lunar terrain. Feature extraction was done to capture the features of each crater. After annotation, each dataset was reviewed to eliminate inconsistencies, ensuring precise and accurate ground-truth labels.

To improve the model's capacity to generalize, a range of data augmentation techniques was applied. Rotation and flipping simulated different orientations of the craters to increase variability. Brightness and Contrast Adjustments simulated different lighting conditions on the lunar surface. Scaling and cropping addressed variations in crater sizes, including those partially visible at the edges of images.

The original high-resolution lunar images were split into smaller tiles, each sized at 512x512 pixels. This segmentation allowed for better identification of smaller craters and ensured that all details in the images were preserved. Additionally, this approach facilitated parallelized processing during model training, improving computational efficiency. A total of 1400 images were generated, out of which 70% went into training, 20% into validation, and 10% for testing. The training dataset served as the foundation for training the crater detection model, providing accurate examples for the model to learn from.

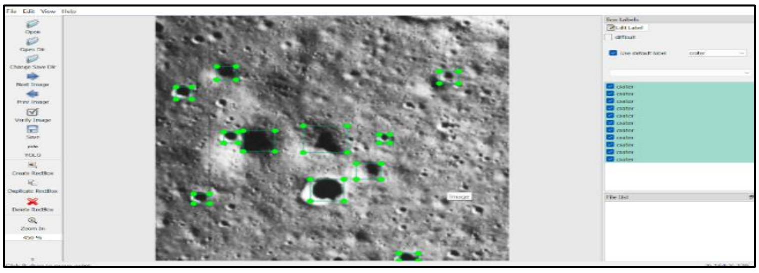

Figure 4. Crater Marking using Label Img Tool

3.3 Crater Detection and Analysis using YOLOv8-CCNET

For real-time object detection applications, such as recognizing craters in lunar images, modern object-detection algorithms like YOLOv8 are preferred due to their effectiveness. YOLOv8 is an advanced deep learning model explicitly designed for these tasks. The model was trained with a generated training dataset, allowing it to extract the distinct features of lunar craters as it goes.

In order to differentiate craters from other lunar features, the CNN then selects relevant features from the image segment. Bounding boxes surrounding possible crater locations are predicted by the proposed model, which also provides confidence scores indicating the model's level of assurance for each prediction. Because of its simplified pipeline, the proposed model is a useful tool for analyzing the lunar surface since it can locate craters with accuracy in real time. Through the use of deep learning techniques, YOLOv8 has improved capacity to identify and characterize lunar features automatically, which advances the knowledge of the surface dynamics and geological history of the Moon. The architecture of YOLOv8 is shown in Figure 5.

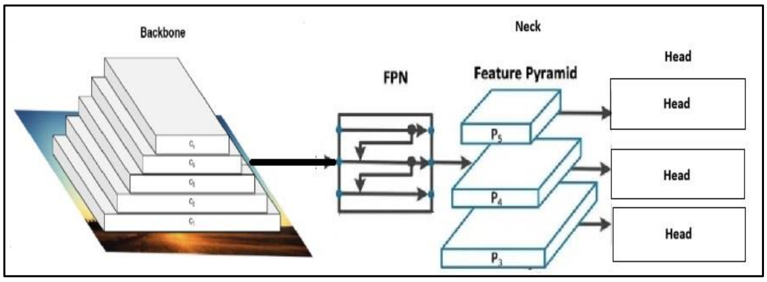

Figure 5. Architecture of YOLOv8 [30]

An important feature of the proposed model is that it directly predicts the centre of an object instead of the offset from a known anchor box. There are 3 essential blocks in the algorithm which are: Backbone, responsible for extracting meaningful features from input images, Neck, that performs feature aggregation and is connecting link between the head and backbone, and finally the Head, that generates network’s output.

CSPDarknet

The proposed model uses an updated version of the CSPDarknet backbone, which has been optimized for better feature extraction while maintaining computational efficiency. This backbone introduces more efficient convolutional layers and integrates Cross Stage Partial connections, which help to lessen the amount of computation while preserving accuracy.

Depth-wise Convolutions

The proposed model uses depth-wise separable convolutions, which decompose standard convolutions into depth-wise and point-wise operations, leading to a significant reduction in the number of parameters and FLOPs (Floating Point Operations).

PANet with Path Aggregation

The proposed model features an improved Path Aggregation Network (PANet) for better multi-scale feature fusion. This architecture improves the flow of features from lower layers to higher layers, increasing the model's ability to detect objects of different sizes.

BiFPN

The introduction of Bidirectional Feature Pyramid Networks (BiFPN) allows the network to aggregate features more effectively from different scales, further improving detection performance on small and large objects.

Decoupled Head

The proposed model adopts a decoupled head structure where the classification and localization tasks are separated into different branches. This separation helps the network to specialize more effectively in each task, leading to improved accuracy.

Efficient I/O

The head is designed to be more efficient in its computation, reducing the latency and making the model faster without sacrificing accuracy.

Anchor-Free Design

The proposed model adopts an anchor-free design, which simplifies the network by removing the need to manually set anchor boxes. This leads to easier training, reduces hyperparameter tuning, and often improves performance, particularly on datasets with varying object sizes.

To optimize YOLOv8-CCNet for the specific task of detecting lunar craters, the architecture was customized as follows:

- Feature Extraction Backbone: Additional convolutional layers were added with smaller kernel sizes to capture finer details such as crater edges and textures. Instead of using regular square-shaped filters (which look at square patches of pixels), this custom layer uses circular-shaped filters to focus on round features in the image. A square grid was built. For each point in the grid, the distance between the point and center of circle was calculated. If a point is within the radius (like inside a circle), it was marked as 1, otherwise 0. The result was a binary 2D mask that looks like a circle in the middle of a square. The pixels outside the circular region were ignored. Also, initial layers used the Leaky ReLU activation function to better handle variations in pixel intensities.

- Feature Pyramid Network (FPN): The FPN was enhanced by introducing a fourth resolution scale. This adjustment improved the detection of both small micro-craters and large craters within the same model framework.

- Adaptive Anchor-Free Mechanism: The model was adapted to use an anchor-free mechanism that focused on center-based predictions. This adjustment proved beneficial for detecting circular and elliptical craters on the lunar surface.

- Loss Function: A custom Intersection over Union (IoU) loss function was implemented to emphasize accurate bounding box localization, particularly for smaller craters that tend to be harder to detect.

- Fine-Tuning Pre-Trained Weights: The model was initialized with pre-trained weights. Fine-tuning these weights on the lunar crater dataset helped accelerate the training process and enhanced the model's ability to adapt to new task.

These improvements made the proposed model more efficient, flexible, and accurate, particularly in challenging object detection scenarios involving varying object sizes, complex backgrounds, and real-time requirements. When presented with a new lunar image segment, the YOLOv8-CCNET model follows a specific pipeline. First, image preprocessing confirms that the image is in the expected format for the model. Then, the CNN extracts relevant features from the image segment, which are essential for distinguishing craters from other lunar features. The model predicts bounding boxes around potential crater locations and assigns confidence scores that reflect the model's certainty about each prediction. Optional post-processing techniques can be applied to further refine the results. Figure 6 shows graphs for training/validation box loss, training/validation class loss, precision, mAP, recall as obtained after training the model.

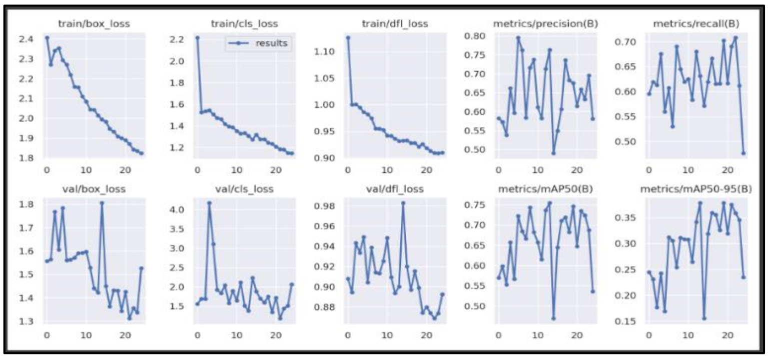

Figure 6. Training Graphs of the Proposed Model

During training, the model ingested the labelled data, learning to recognize the unique features of craters. After the training process, the model's performance was evaluated over a different set of lunar images not used in training phase. This evaluation determined the model's ability to apply its innovative knowledge of crater detection to unseen data. The model achieved significant success, with the trained model achieving a 90% accuracy rate in identifying craters within the test images.

4. Results and Discussion

For better understanding how the proposed model worked as compared to other models, a comparison based on five performance metrics – Recall, Precision, Accuracy, F1-score, and IoU was performed. The results are given in Table 2. The performance of the model was compared with YOLOv5, Faster RNN, and DeTr ResNet. Confusion matrices, accuracy graphs were compared to get the general idea of selecting the best model for lunar crater detection. As can be seen in Table 2, YOLOv8-CCNET achieved an accuracy of 90%. YOLOv8-CCNET can effectively identify unique crater characteristics in lunar images, utilizing a Convolutional Neural Network architecture specifically customized to detect spherically shaped objects like crater. In the following section, a detailed comparison analysis is presented.

During experimentation, it was observed that YOLOv8-CCNET and YOLOv5 both excel at processing images quickly. Both the models exceled at processing images quickly, making them ideal for real-time object detection tasks. YOLOv5 gave an accuracy of 84% which is lower than the accuracy of the proposed model. YOLOv8-CCNET at 90% accuracy is more accurate than YOLOv5. Figure 7 shows the confusion matrix for the YOLOv8-CCNET and YOLOv5. As depicted in Figure 7, the comparison between YOLOv8-CCNET and YOLOv5 reveals their respective performance metrics in lunar crater detection. The model exhibits a True Positive rate of 0.89, indicating its capability to correctly identify craters, while YOLOv5 shows a True Negative rate of 0.11, suggesting its effectiveness in accurately identifying non-crater areas. Main drawback observed in YOLOv5 is it's incapability to detect smaller craters. Small craters were more accurately detected by the proposed model.

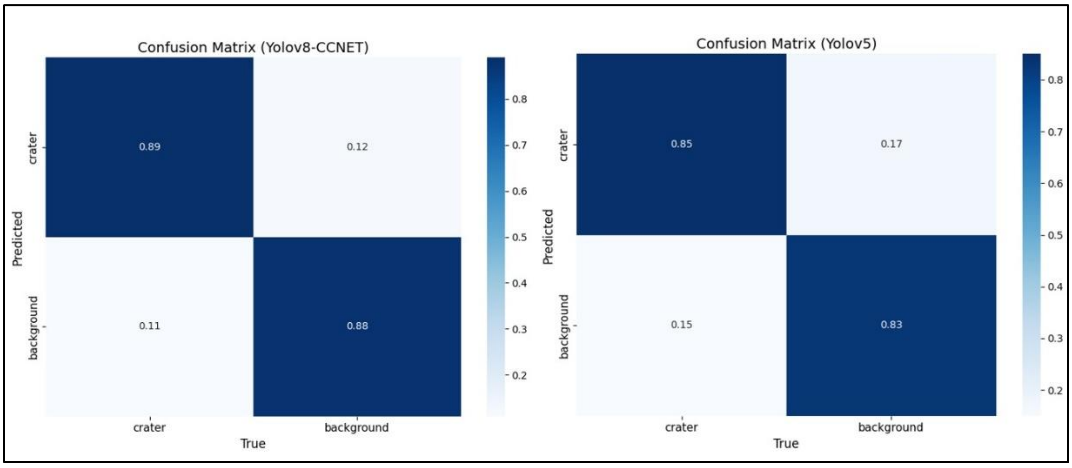

Figure 7. Confusion Matrix a) YOLOv8-CCNET b) YOLOv5

Two more state-of-the-art models used in literature - Faster RCNN and DeTr ResNet were also used for comparison. When compared with Faster RCNN, Faster RCNN produced an 80% accuracy rate on the Detectron model. Detectron is a software system developed by Facebook AI Research that applies cutting-edge object detection algorithms. DeTr ResNet model gave an accuracy of 75%. It is a type of CNN architecture known for its ability to learn from deeper layers. This characteristic can be beneficial for complex image recognition tasks like crater detection. Figure 8 shows the comparison chart for all four models. As observed from the graph, YOLOv8-CCNET gives the highest accuracy. Table 2 gives the detailed comparison statistics.

Table 2. Comparison of Performance Metrics

MODEL	Accuracy	Recall	Precision	F1-Score	IoU
YOLOv8-CCNet	90%	0.9	0.88	0.88	0.75
YOLOv5	84%	0.85	0.83	0.83	0.71
Faster R-CNN	80%	0.8	0.76	0.77	0.68
DeTr ResNet	75%	0.75	0.72	0.73	0.65

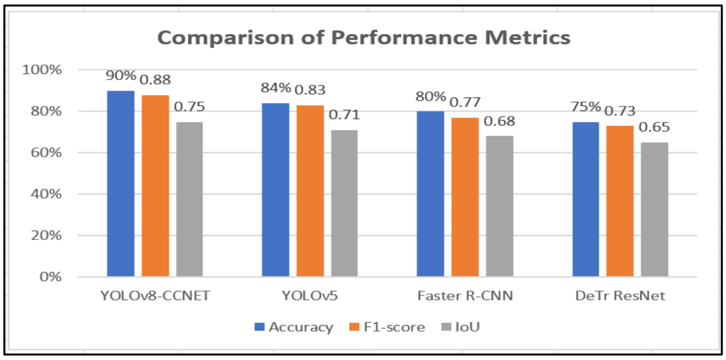

Figure 8. Comparison of Performance Metrics

4.1 Detecting Craters in an Image

To test the effectiveness of the model, the test images were first converted into the proper format. In Figure 9, predictions on a single image are showcased, providing valuable insights into the model's performance and the craters detected within the image. The predictions include their corresponding confidence scores. Confidence scores indicate the model's level of certainty regarding each detected crater. Higher confidence scores typically suggest that the model is more confident in its detection, while lower scores may indicate greater uncertainty. As can be seen in the figure, the predictions given by YOLOv8-CCNET are fairly accurate.

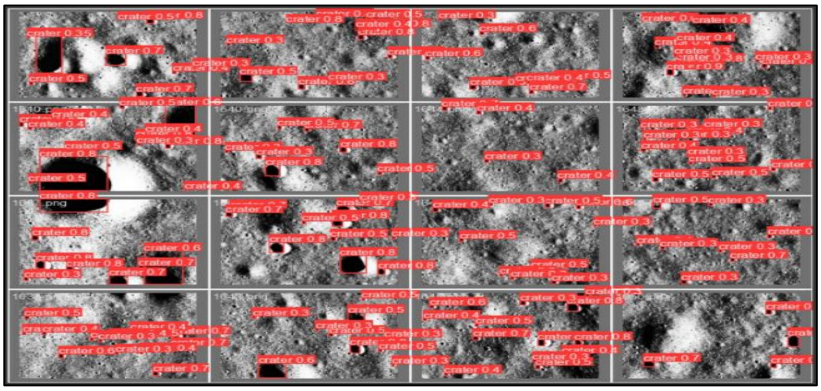

Figure 9. Predictions given by YOLOv8 on a Single Image

5. Conclusion

In conclusion, the methodology proposed in this research provides a thorough strategy for detecting craters on the lunar surface using high-resolution lunar images. the Chandrayaan 2 tool segments the original images into smaller sections, allowing for detailed analysis of regions of interest that may contain craters. The annotation process, supported by LabelImg, is essential in establishing high quality ground truth dataset for training crater detection model. Through annotation, researchers can accurately pinpoint craters and provide precise bounding boxes around them, laying a strong foundation for model training. The integration of YOLOv8, a robust object detection algorithm, with customized CNN specifically designed to detect circular objects, further improves the crater detection process. Trained on the annotated dataset, YOLOv8-CCNET can effectively identify unique crater characteristics in lunar images, utilizing a Convolutional Neural Network architecture to achieve reliable detection capabilities. A rigorous evaluation of the model yields an impressive 90% accuracy rate on a different validation dataset, demonstrating the model's capability to locate and detect craters on the lunar surface. In general, the methodology's successful implementation shows promise for automated lunar crater exploration and analysis. In addition to accurately identifying craters, the automated system will further extend its capabilities to measure the diameters of detected craters. By implementing advanced image-processing procedures and using machine learning algorithms, the system will be able to estimate crater diameters with high precision. This enhancement will provide valuable quantitative data on the size distribution of lunar craters, aiding in geological studies and facilitating comparisons with terrestrial impact cratering processes. This study demonstrates the application of YOLOv8-CCNET for automated lunar crater detection, demonstrating how deep learning models can aid planetary exploration. The customized adjustments to YOLOv8’s architecture, combined with rigorous data preparation and augmentation techniques, resulted in a model that achieved high accuracy. These findings provide a strong foundation for future work in automating planetary feature detection, providing significant insights into the role of deep learning in space research.

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