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Automated Detection of Craters and Boulders Using Machine Learning on OHRC Images

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Abstract:

Detection of Craters and Boulders is a critical task in Space. In earlier times, Counting was performed manually on the images. This Counting takes a lot of time, and the probability of Human error is high. This research aims to automate this process and make it easier for Humans. Making this process fully automated requires state-of-the-art machine-learning algorithms. These algorithms have much efficiency and precision, which results in fewer errors. The help of an Orbiter High-Resolution Camera (OHRC) and Computer Vision techniques make data more accurate for processing. Later, this manuscript applies certain machine learning algorithms such as Support Vector Machines (SVM), Random Forest, and Convolutional Neural Networks (CNN) on these data to detect features such as rocks, craters, and boulders with promising accuracy. The author observes that the Support Vector Machine results (SVM) have a better level of precision. Additionally, this research identifies the most effective algorithm for crater and boulder detection.

Keywords: Orbiter High-Resolution Camera (OHRC), Computer Vision, Machine Learning, Crater detection, Boulder detection, Support Vector Machine.

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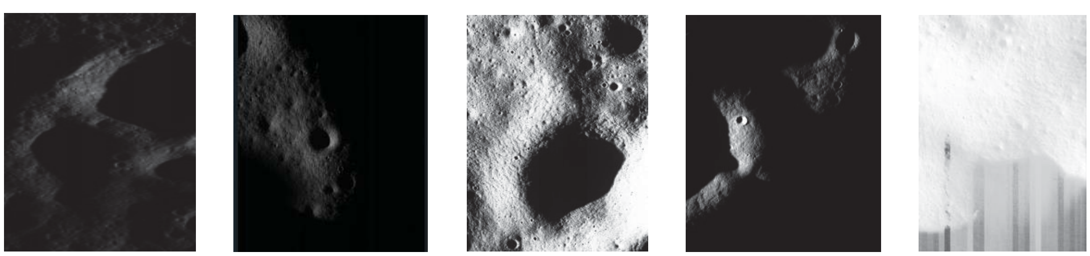
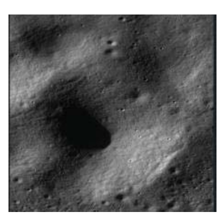
Introduction:

The most fundamental elements of Space are Craters and boulders. The study will help to understand the condition of surfaces. Craters are formed by the impact of asteroids on the planet's surface. Boulders are scattered across multiple planetary surfaces, resulting from events like landslides and erosion. Their size, shape, and composition can reveal much about the planet's history, the Nature of Space, and its activity. In Figure **1(a)**, an illusion due to the presence of shadows making it the false appearance of a crater, but no crater is present, displays the correct response by returning a false result. In Figures **1(b)** and **1(c)**, craters are detected, although some features point to noise or illusions, with some possibility of small boulders. Figure **1(d)** shows that both small craters and boulders, with the sand formation, identified the presence of a boulder. Figure **1(e)** Completely contains noise, so here the techniques of computer Vision are applied to get the number of craters and boulders. Finally, Figure **1(f)**, displays the presence of both boulders and deep craters, along with small-sized craters.



(A) (B) (C) (D) (E)



(F)

Figure 1: Images of Boulders and Craters : (a) Illusion (No crater), (b) Small Craters, (c) Small and big craters, (d) Small Crater and Boulder (e) Noisy Image, and (f) Boulder and Crater.

In past decades, various techniques have been applied to automate crater and boulder detection, but some of these approaches face challenges. Earlier techniques, such as edge detection and image segmentation, are used much to identify craters and boulders, but these struggle a lot with accuracy, due to noise presence, shadows or maybe illusion, and the dynamic textures of planetary surfaces (**Chen et al., 2022; Collins et al., 2022**). CNN is the most used model for feature recognition in high-resolution images.

Earlier studies, which primarily relied on single-spectrum images, this model integrates data coming from multiple spectral bands such as infrared (IR) and Ultraviolet (UV), etc., enabling more comprehensive detection of planetary features across multiple conditions (**McEwen et al., 2023; Smith et al., 2022**). The author also added advanced noise reduction techniques and trained this model on a broad set of high-resolution orbital images from different planet's orbital missions. This general approach allows this model to gain more effectively to diverse planetary land, reduce false positives, and improve accuracy. This detection system for both craters and boulders offer faster and more reliable geological data analysis, Previous methods, treat these features separately (**Hall et al., 2023; Jones et al., 2023**).

Motivation:

The motivation for the research is to increase the speed and accuracy of detecting Craters and Boulders in planets. By enhancing innovative techniques, this research aims to enhance detection accuracy and make it enable real-time decision-making on space missions. These methods can be chosen for Earth-based applications, such as monitoring natural disasters, studying erosion, and tracking geological changes, making research valuable for both planetary bodies and terrestrial science.

Literature Review

Crater and boulder detection has historically relied on time-consuming methods. Researchers have tried many automated techniques using machine learning algorithms to increase the efficiency and accuracy of detecting Craters and Boulders. The importance of moving towards an approach for the detection of Craters and Boulders across various studies reflects the need to choose methods according to dataset characteristics. This is clearly explained by **Lechner**

and Völz (2021) by using synthetic data to train their model, and the computer-generated data shows more accurate observations. The performance tested on spacecraft navigation and got good results, which means the characteristic plays an important role. Furthermore, the work of **Xu and Zhang (2021)** on transfer learning revealed its potential to boost model efficiency, especially when labeled data is limited. Their findings indicate that training models on extensive datasets beforehand can enhance their adaptability to particular tasks, thus improving the accuracy of crater detection in high-resolution images acquired from space missions.

Chen et al. (2022) focused on multispectral Images that show different forms of images and observation increased due to the presence of multispectral lines. They tested on various models such as Random Forest, Support Vector Machines, and k-Nearest Neighbour for craters and boulder detection on Mars. Their research shows a better level of accuracy and precision by Random Forest and SVM. In parallel, **Collins et al. (2022)** research focuses on various algorithms and reveals that combining image-processing approaches mainly focuses on CNN, as they are good in object detection after that they match with manually annotated data which shows very significant good results. While Support Vector Machines have shown promising results, many researchers tested CNN for this task. For instance, **Smith et al. (2022)** focus on the detection of boulders in High-resolution Mars Orbiter images using Deep learning approaches. They train the model on training data that contains both annotated data (collected manually) and high-resolution images. The results show a high level of accuracy in these crater searches. In the same way**, Meyer and Renshaw (2022)** further explain the importance of a hybrid model in these crater detection systems. The research compares both manual methods and hybrid models to predict the correct and accurate output. **McEwen et al. (2023)** explored CNN models for the detection of craters in high-resolution satellite imagery, reporting a high level of efficiency in feature detection. They found that CNN was particularly focused on identifying complex patterns that traditional algorithms may not find. Their work also indicated that CNNs can yield higher recall rates, and SVM demonstrated superior precision in some cases, underscoring the need for a method depending on the dataset characteristics. **Thoma et al. (2023)** focus on real-time feature extraction Their research explains the advancement of Crater and Boulder detection Algorithms, their research Uses Neural Network models such as CNNS to classify the craters on Images.

O'Reilly and Wong (2024) focus on CNNs specifically for the detection of craters in lunar, their research classifies that CNNS have a good level of accuracy in detecting craters. **Rodriguez and Smith (2024)** focused on a hybrid approach that integrates deep learning techniques with traditional image processing methods such as filtering, morphological operations edge detection, etc. This Combination provides an effective way for crater detection, addressing the complexities presented by varied lands in planetary exploration.

Methodology:

The methodology of this research provides an overview from **Data acquisition** to result **visualization.** From **data acquisition** to **data processing,** it is very important that data must be free from noise and for removal and reduction of noise. The **Gaussian blur technique** and **edge detection** methods are used to clean data. Applying state-of-the-art machine learning techniques and **computer vision techniques**, results in an excellent level of accuracy, and some of them result in a good level of precision by comparing a certain number of parameters for analysis, finally, Analysis gives results in the best algorithm which we can use for detection of crater and boulder. **Chandrayaan-2 Orbital High Resoultion camera(OHRC) Dataset** taken form **ISSDC (Indian Space Science Data Center) and NASA LRO** dataset. Our purpose is to detect Crater and Boulder for this we require high-resolution Images as outlined in Figure 2. Further, it consists of three steps of model selection as depicted in Figure 3.

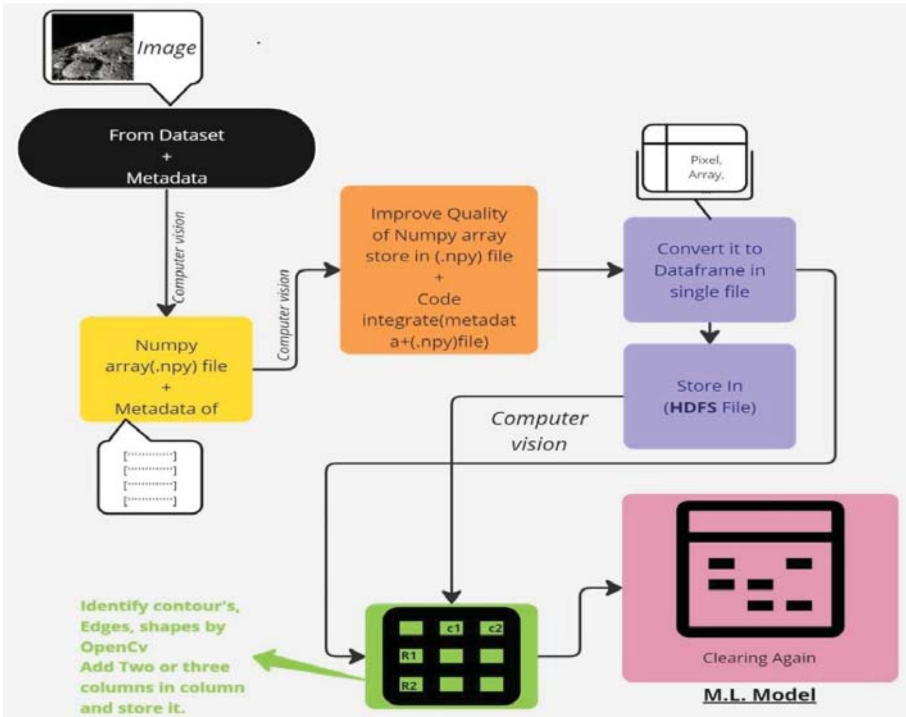


Figure 2: Proposed model

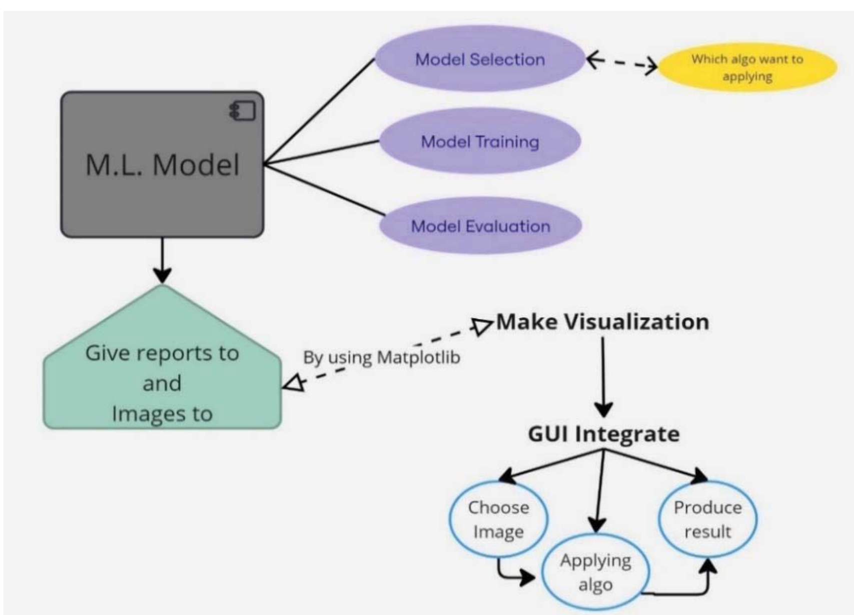


Figure 3: Model selection process in the proposed model

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Pseudo code of proposed model:

```
FUNCTION STrain(Xtrain, ytrain, C, kernel_type):
 Initialize weights (w) and bias (b), learning rate (alpha)
 Initialize maximum number of iterations (max_iter), tolerance (tol)
FOR iteration from 1 to max_iter:
 For each sample (x_i, y_i) in (Xtrain, ytrain):
 margin = y_i * (dot_product(w, x_i) + b)
 IF margin >= 1: w = w - alpha * (2 * lambda * w)
 ELSE: w = w - alpha * (2 * lambda * w - y_i * x_i)
 b = b + alpha * y_i
 IF ||update|| < tol:
 BREAK RETURN (w, b)
FUNCTION SPredict(Xtest, w, b):
 predictions = []
 For each sample x in Xtest:
 score = dot_product(w, x) + b
 IF score >= 0: predictions.append("Crater")
 ELSE: predictions.append("Boulder")
 RETURN predictions
 END
```

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Dataset preparation:

Data acquisition- Higher Resolution Images taken by ISRO Orbital High-Resolution Camera along with its metadata file. The data sources included:

Chandrayaan-2 Mission:

Images Collected: 208

Metadata Availability: Yes (includes coordinates, projections, Geometry, etc.)

Image Resolution: 0.25 meters/pixel

Swath Width: 3 km

Swath Width-width cover by machine on the surface of the Planet.

NASA Lunar Reconnaissance Orbiter (LRO):

Total Images Collected: 50

Metadata Availability: Yes

Resolution:

Narrow-Angle Camera: 0.5 meters/ pixel

Wide Angle Camera: 100 meters/ pixel

Data organization- The Data is acquired in the form of images after data acquisition and organization takes place. These data frames are stored in HDF5 file format which helps us to analyze the data and also helps us to manipulate it. **Additionally, s**uccessfully Gathered Information in the form of Images that will further move Data preprocessing steps and data Visualization.

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Table: 1 Data preprocessing.

Data Sources	Total Images	Metadata Availability	Resolution
Chandrayaan-2 (OHRC)	208	Yes	0.25 meters/pixel
NASA LRO	50	Yes	Narrow Angle: 0.5 meters/pixel Wide Angle: 100 meters/pixel

Results:

The observation is that the accuracy of CNN is better than the SVM model. However, the Precision of SVM is greater than the precision of CNN. The result outlined in Figure 4 highlights the comparison of SVM accuracy and CNN accuracy.

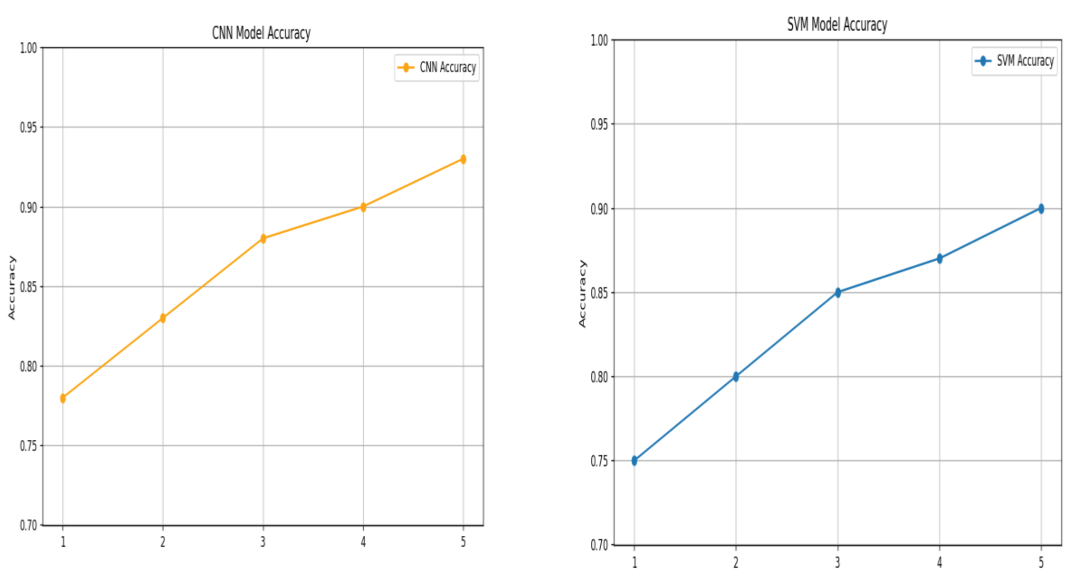

Figure 4: Comparison of CNN and SVM.

Conclusion:

In conclusion, the proposed model that results in the maximum level of accuracy and Precision. Also, the author observed that these Machine Learning and Image-Processing techniques can be applied to various domains where there is very little possibility of the existence of space ex-Blackholes, Nebula, etc. After, analysis the results are outlined in the form of a graph to highlight the comparison.

Acknowledgments:

I would like to thank PSIT Kanpur for facilitating this research and to Professor Dr. Nand Kishore Sharma for guiding us from starting of our project till their Results. I would like to show gratitude to the PSIT Vyomnauts Club for their support in exploring this Dataset.

Conflict of Interest:

The authors confirm that there are no conflicts of interest regarding the publication of this research paper. All the work has been carried out with full integrity and objectivity. Furthermore, none of the authors' findings were influenced by any financial or personal relationships that could have biased the results or interpretation.

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