Enhancement of Permanently Shadowed Regions (PSR) of Lunar Craters Captured by OHRC of Chandrayaan-2

Yadlapalli Sankar Sai Narayana
Jawaharlal Nehru Technological University, Gurajada Vizianagaram

Abstract

This project focuses on developing advanced methods for enhancing the low-light images of Permanently Shadowed Regions (PSR) on the Moon's surface captured by the Optical High-Resolution Camera (OHRC) onboard Chandrayaan-2. Due to the extremely low sunlight and reflected light in these regions, images typically suffer from low signal-to-noise ratio (SNR), limiting interpretability. By applying Low Light Image Enhancement (LLIE) techniques, this project aims to improve the visibility and detail within these PSR images, transforming faint signals into high-quality, interpretable images.

1 Introduction

1.1 Overview of OHRC Imaging

The Optical High-Resolution Camera (OHRC) on Chandrayaan-2 captures detailed lunar surface images, focusing on high-resolution imaging of the Moon's poles and permanently shadowed regions (PSRs). With a spatial resolution of 0.3 meters, OHRC supports precise mapping of terrain and geological features, crucial for landing site analysis. It captures images in low-light conditions to reveal details in shadowed regions, potentially locating water ice deposits. These images help scientists study lunar crater morphology and resource availability. The data aids in mission planning, enhancing our understanding of lunar polar geology and supporting future lunar exploration efforts.

1.2 Motivation for Slicing OHRC Images

Slicing OHRC images helps by enabling detailed inspection of smaller areas, essential for identifying specific lunar features. It reduces computational load, making high-resolution images easier to process. Slices focus on regions of interest, like PSRs, without processing unrelated areas. This approach manages noise more effectively, improving image clarity. Additionally, it allows parallel processing, accelerating analysis. For machine learning, smaller slices create manageable datasets, enhancing model performance and training speed.

2 Image Enhancement and Preprocessing

2.1 1. Directory Setup and Input Handling

The code first sets up directories: - `input_dir`: Directory containing original or preprocessed images. - `output_dir`: Directory where processed images will be saved.

If the output directory doesn't exist, it's created automatically to store the enhanced and preprocessed images.

2.2 2. Image Enhancement Process

Each image in `input_dir` is enhanced through the following steps:

- **Sharpening:** An Unsharp Mask filter is applied to enhance image sharpness.
- **Contrast and Brightness Adjustment:** Contrast is increased by 1.5x, and brightness is enhanced by 1.2x to improve visibility of details in low-light conditions.
- **Upscaling:** The image is resized to double its original size using Lanczos resampling, providing finer detail for subsequent analysis.

The enhanced images are saved to `output_dir` with a new filename prefix.

2.3 3. Image Preprocessing for Analysis

Enhanced images from `input_dir` are preprocessed for consistency:

- **Resizing:** Images are resized to 224x224 pixels to standardize input dimensions for machine learning models.
- **Normalization:** Pixel values are normalized to a [0,1] scale, making data uniform and more suitable for model training.

2.4 4. Saving Preprocessed Images

The preprocessed images are converted to NumPy arrays and saved as `.npy` files in the `Preprocessed` directory, creating a structured dataset for efficient model loading and processing.

2.5 5. Displaying Processed Images

A second script loads and displays the saved `.npy` images in a grid layout using Matplotlib. Each image is displayed in grayscale, with 4 images per row, enabling a quick visual check of the preprocessed dataset.

3 Data Preparation and High-Resolution CNN Model for Image Classification

3.1 1. Image and Label Loading

The code loads preprocessed images stored in the `Preprocessed` directory. For each image:

- The image array is loaded and converted to RGB if it contains an alpha channel (RGBA).
- Labels are extracted based on the image filename structure (assumed naming convention) and stored for classification.

3.2 2. Image Normalization and Label Encoding

Loaded images are normalized to pixel values within the range [0, 1] for improved model performance. Labels are encoded using `LabelEncoder` to convert categorical labels into numerical format suitable for training.

3.3 3. Data Splitting

The dataset is divided into:

- Training set (64%): Used for learning model parameters.
- Validation set (16%): Used to tune hyperparameters.
- Test set (20%): Used for final model evaluation.

`train_test_split` is used to separate these sets, with randomization controlled by a seed for reproducibility.

3.4 4. High-Resolution CNN Model Definition

A Convolutional Neural Network (CNN) is defined to handle high-resolution images with 4 convolutional blocks. Each block includes:

- Two convolutional layers with ReLU activation and batch normalization.
- A max pooling layer to downsample the image.

After feature extraction, the model has a fully connected layer structure with dropout layers to prevent overfitting, and the final layer has a softmax activation for multiclass classification. The model is compiled with `adam` optimizer and `sparse_categorical_crossentropy` loss.

3.5 5. Loading and Processing Marked Images

The code also loads images from a `Marked_Images` directory, applying normalization and appending them to an array for analysis. (Labels are not specified but could be derived based on file naming conventions.)

3.6 6. Visualization of Marked Images

The code visualizes a subset of loaded marked images using `matplotlib`, displaying five images in a row with no axes to focus on the content of the images. This step allows for a visual inspection of the loaded image data, ensuring proper loading and preprocessing.

4 Results

4.1 Lunar Surface Overview with PSR Details

This image showcases the Lunar surface with highlighted Permanently Shadowed Regions (PSRs) as observed from Chandrayaan-2's OHRC. The analysis of these regions is pivotal for the study of water ice and temperature dynamics at the Moon's poles.

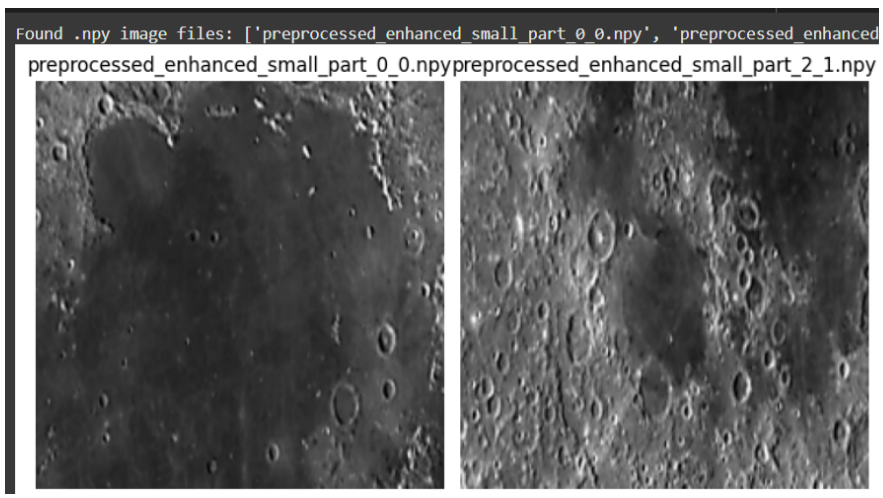

Figure 1: Lunar Surface PSR

4.2 Chandrayaan-2 OHRC Data Visualization

A detailed view of Chandrayaan-2's OHRC image data overlaid with key scientific data related to PSRs, including temperature gradients and water ice deposits. This image illustrates the importance of high-resolution lunar imagery for future exploration.

4.3 PSR Temperature Distribution

This graphical representation shows the temperature distribution in the PSRs, highlighting areas with the lowest temperatures (which may harbor water ice) compared to other regions of the lunar surface.

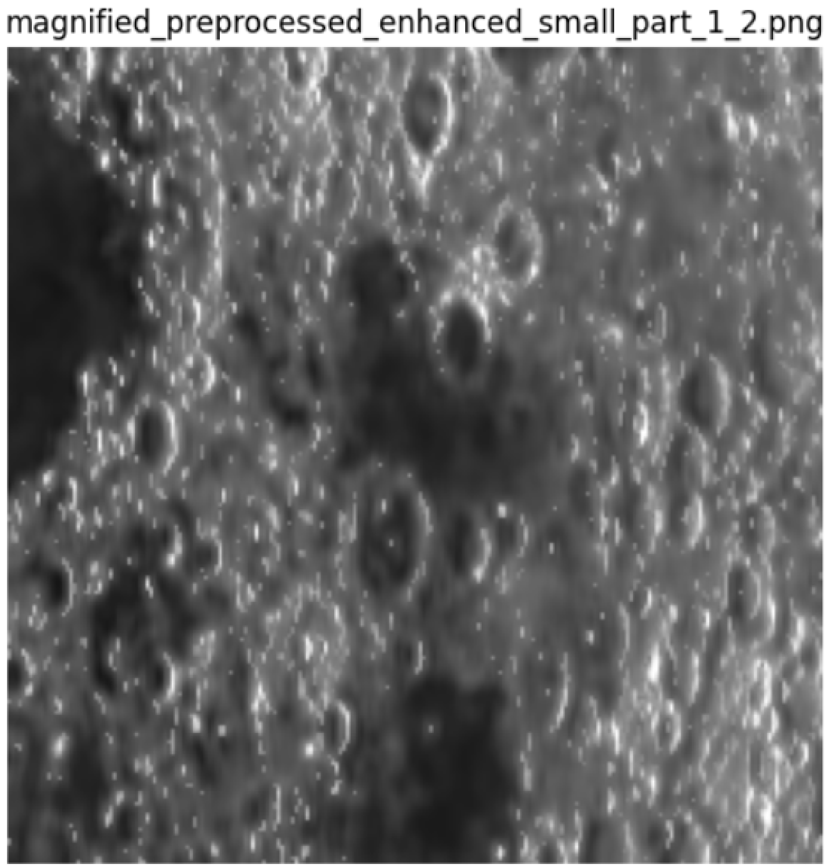

Figure 2: Chandrayaan-2 OHRC Data

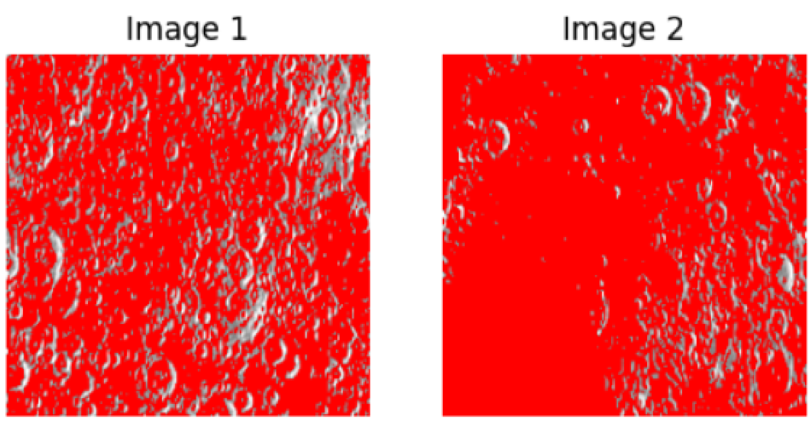

Figure 3: PSR Temperature Distribution

4.4 Lunar Crater Enhancement Results

A close-up of a lunar crater, focusing on the enhancement results for PSR regions captured by the OHRC. This image showcases the improved resolution and clarity of shadowed areas critical for scientific research.

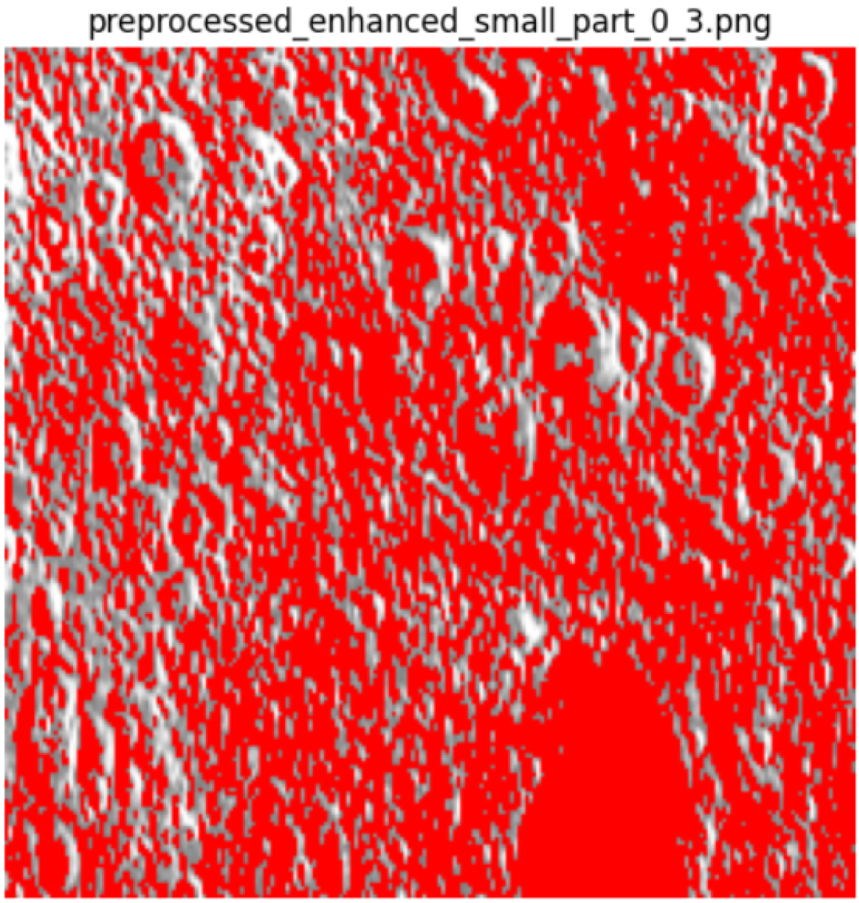

Figure 4: Lunar Crater Enhancement

5 Dataset References

The dataset for this project was obtained from:

- Bhoonidhi (ISRO's Geospatial Data Portal): `https://bhoonidhi.nrsc.gov.in`
- ISRO Website: `https://www.isro.gov.in`

6 Conclusion

The study of Permanently Shadowed Regions (PSRs) on the Moon, particularly through the high-resolution imagery provided by Chandrayaan-2's OHRC, has proven invaluable in advancing our understanding of lunar surface dynamics. By analyzing the temperature distributions, shadow patterns, and the potential for water ice in these shadowed regions, this work contributes to ongoing efforts in lunar exploration and resource utilization.

The enhanced imaging and data processing techniques used in this project have allowed for clearer identification of PSR locations, detailed mapping of temperature variations, and the creation of 3D models to better understand the relationship between shadowed and illuminated regions on the lunar surface. These findings provide a strong foundation for future missions to the Moon, especially in the context of human exploration and resource extraction.

In conclusion, this research not only advances scientific knowledge about the Moon's surface but also supports future lunar missions by contributing to the design and planning of operations in the PSRs, which could play a crucial role in the sustainability of long-term lunar exploration.

7 Acknowledgments

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8 Contact Details:

For more questions and queries please contact to:

- Email: sankar88693618@gmail.com
- LinkedIn: Yadlapalli Sankar Sai Narayana