Basic Details of the Team and Problem Statement

Ministry/Organization Name: State Ministry

PS Code: SIH1519

Problem Statement Title: Generation of Hazard Map

Team Name: Valtreyak Sprryzen

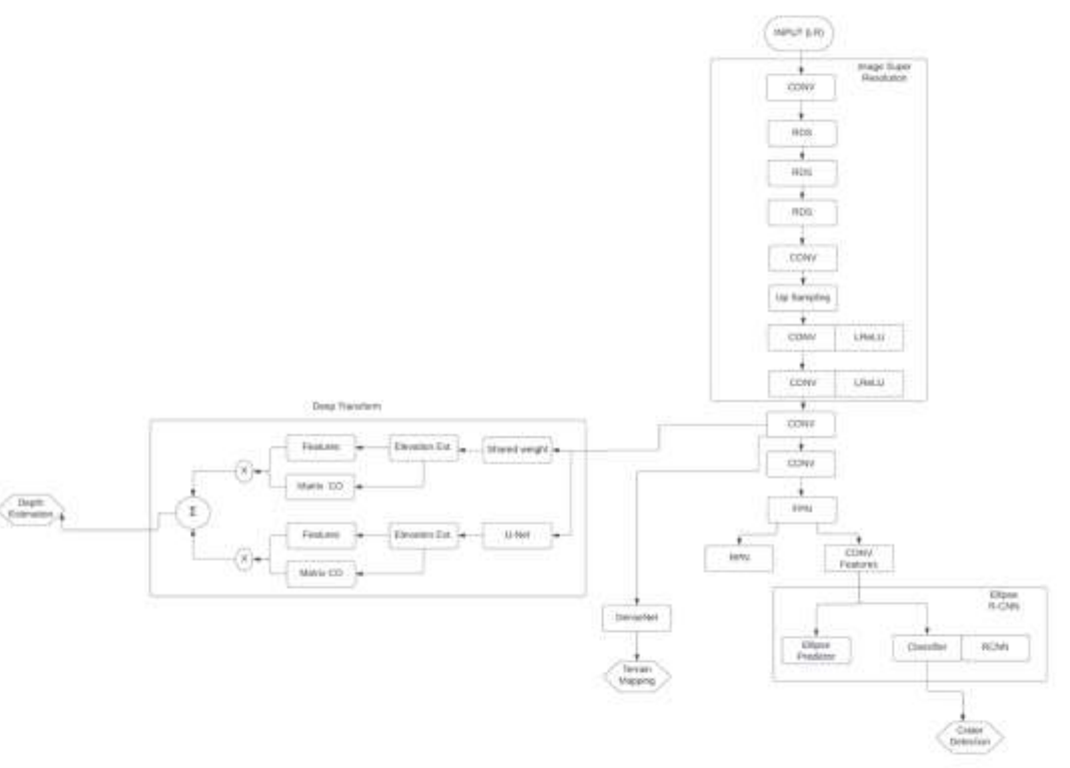
Team Leader Name: Rahul Kumar Singh

Institute Code (AISHE): U-0954

Institute Name: Indian Institute of Information Technology, Surat

Theme Name: Space Technology (Software)

Idea/Approach Details



Describe your idea/Solution/Prototype here:

- ➢ Aim: To provide create hazard map (crater detector)
- ➢ Reasons: To help with safe navigation of lander.
- ➢ Solutions:
  - <u>Super Resolution</u>: To upscale the image resolution for further processing.
  - <u>Crater Detection:</u> To detect crater help in securing a safe route avoiding the craters.
  - <u>Terrain Mapping </u>: To map the terrain and get all the geographical information about the moon.
  - <u>Hazard Map</u>: Creation of Hazard map using the results from Crater Detection and Terrain Relative Navigation.
  - <u>Crater Mapping</u>: To identify the pattern in the craters to provide faster crater recognition.
  - <u>Terrain Classification:</u> It is useful for route planning and obstacle avoidance.
  - <u>Depth Estimation:</u> Pix2Pix - GANs are used for depth estimation of moon's surface from the relative position at which the image was captured.

Describe your Technology stack here:

- ➢ Python → Foundation for the given models.
- ➢ Ellipse R-CNN → Used for Crater Detection..
- ➢ GANS → Used for Super Resolution and Depth Estimation.
- ➢ OpenCV → For using pre-trained Computer Vision Models.
- ➢ DenseNet → Terrain Classification
- ➢ Keras → Used for Deep Feature Extraction

Idea/Approach Details

Describe your Use Cases here

- Identifying Lunar Surface Features like craters depth, boulder, rifts, slope to help avoid hazards during lunar navigation.
- Image Super Resolution: To upscale and improve the quality of low resolution images taken by terrain mapping cameras
- Crater Detection: To Identify crater rim from the high resolution images (from ISR).
- Elliptical R-CNN includes two components - Mask R-CNN for elliptical Object retrieval and U-Net Semantic Segmentation) for learning different occlusion patterns
- Terrain Classification: DenseNet is used to segregate the images into different segments based on CNN.
- Depth Estimation: Pix2Pix and GANs are used for depth estimation of moon's surface

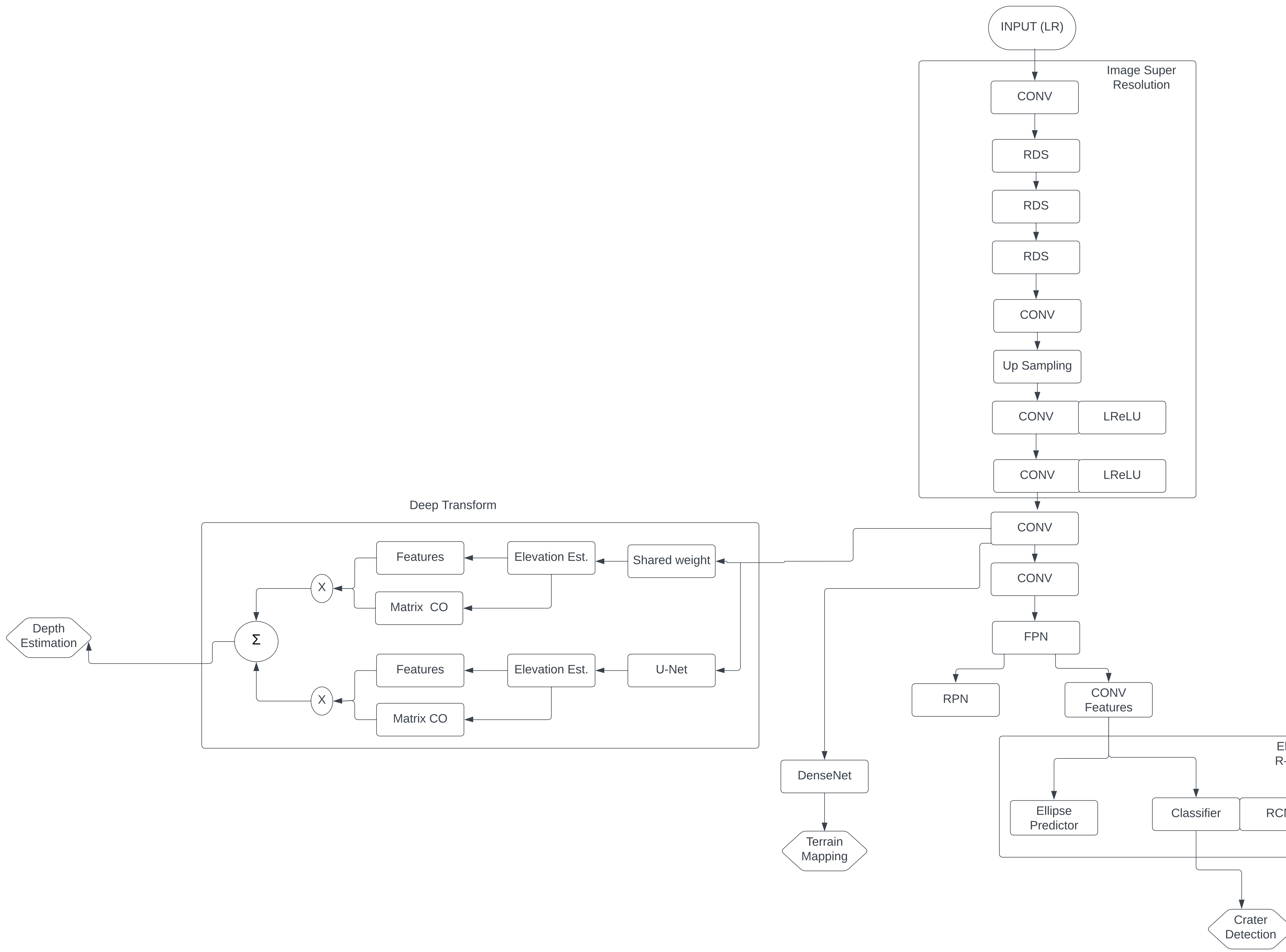
Describe your Dependencies / Show stopper here

Task Dependencies:

- ML models (Deep Learning Models).
- Computational Resources.
- Fine tuning of Generative models.
- Image Processing.

Show Stopper:

- Feature-based transform is harder to train, and require some hyperparameter tuning and loss balancing
- Lighting Conditions: Moon's surface has areas of permanent shadow or of strong sunlight.
- Regular Updates: Due to the dynamic environment of the moon.
- To improve the resolution of the images from terrain relative cameras.



INPUT (LR)
Image Super Resolution
CONV
RDS
RDS
RDS
CONV
Up Sampling
CONV
LReLU
CONV
LReLU
CONV
CONV
FPN
RPN
CONV Features
Ellipse R-CNN
Ellipse Predictor
Classifier
RCNN
Crater Detection
DenseNet
Terrain Mapping
Deep Transform
Shared weight
Elevation Est.
Features
Matrix CO
X
Σ
U-Net
Elevation Est.
Features
Matrix CO
X
Depth Estimation

Hazard Maps

Mapping the Moon's Hazards

Creating hazard maps is the first step in safely navigating a lunar lander. These detailed maps help us identify potential risks and plan our landing strategy effectively.

Super-Resolution Techniques

To overcome the challenge of working with lower resolution data, we employ super-resolution techniques. These methods enhance the quality of lunar images, making them suitable for further analysis and

Utilizing Super-Resolution

The super-resolution techniques we use involve advanced deep learning models, particularly the powerful Keras framework. By leveraging generative adversarial networks (GANs), we can improve image resolution and sharpness.

Crater Detection

1

Identifying Lunar Hazards

Crater detection is essential for terrain relative navigation and hazard avoidance during lunar landings. We employ sophisticated computer vision models to identify and analyze craters in high-resolution lunar images.

2

Elliptical Object Retrieval

Our crater detection model utilizes the Ellipse R-CNN, a powerful model that combines Mask R-CNN for elliptical object retrieval and U-Net Semantic Segmentation for learning occlusion patterns within crater images.

3

Enhancing Accuracy with OpenCV

To ensure accurate crater identification, we leverage pre-trained computer vision models from OpenCV. These models assist us in precisely detecting and analyzing craters on the lunar surface.

Crater Matching

1

Identifying Crater Patterns

Once craters are detected, we focus on identifying patterns within these unique lunar features. This aids in faster and more accurate recognition of craters, enhancing the navigation process and improving hazard assessment.

2

Advanced Pattern Recognition

We employ advanced pattern recognition algorithms that analyze the shape, size, and distribution of craters on the moon's surface. This enables us to identify and match craters with precision.

3

Improving Navigation Efficiency

By identifying and matching crater patterns, we can optimize the navigation process. This allows for more efficient and safer lunar landings, reducing the risks associated with unfamiliar lunar terrains.

Visual Terrain Relative

Identifying Lunar Surface Features

In addition to crater detection, we identify other critical lunar surface features such as boulders, rifts, and slopes. This information helps with route planning and obstacle avoidance.

Depth Estimation for Safety

Depth estimation is crucial for visual terrain relative navigation. We employ advanced machine learning techniques, such as Pix2Pix and GANs, to determine the depth of the moon's surface relative to the camera's position, enhancing safety and precision.

Terrain Classification

To classify different types of lunar terrains, we utilize DenseNet, a state-of-the-art convolutional neural network architecture. This segmentation technique helps us plan routes and avoid potential obstacles.

Challenges and Dependencies

1. ## Fine-Tuning for Optimal Results

While our approach shows promise, feature-based transformations like super-resolution require tuning and balancing to achieve optimal results. Continual refinement and improvement are necessary to enhance the quality of lunar navigation.

2. ## Dealing with Lunar Lighting Conditions

Lunar lighting conditions pose challenges for image analysis. Areas of permanent shadow and intense sunlight require adaptive algorithms to ensure accurate detection of lunar features.

3. ## Continual Research and Updates

The dynamic lunar environment requires regular updates to our navigation system. As we learn more about the moon and its terrains, we continuously refine our methods and models to ensure the safety and success of lunar missions.

Cutting-Edge Technology for Lunar Navigation

Deep Learning Models (Keras)

Our lunar navigation system heavily relies on deep learning models to process and analyze lunar images. These models enable us to accurately detect and classify various lunar features.

Ellipse RCNN

Ellipse R-CNN is a specialized technology stack for object detection. It is commonly employed in applications such as crater detection. Leveraging Region-based Convolutional Neural Networks (R-CNN) principles, Ellipse R-CNN excels in accurately locating and classifying elliptical objects, making it a valuable tool for tasks requiring precise shape recognition, such as identifying craters in satellite imagery.

Fine-Tuned Generative Models (GANs)

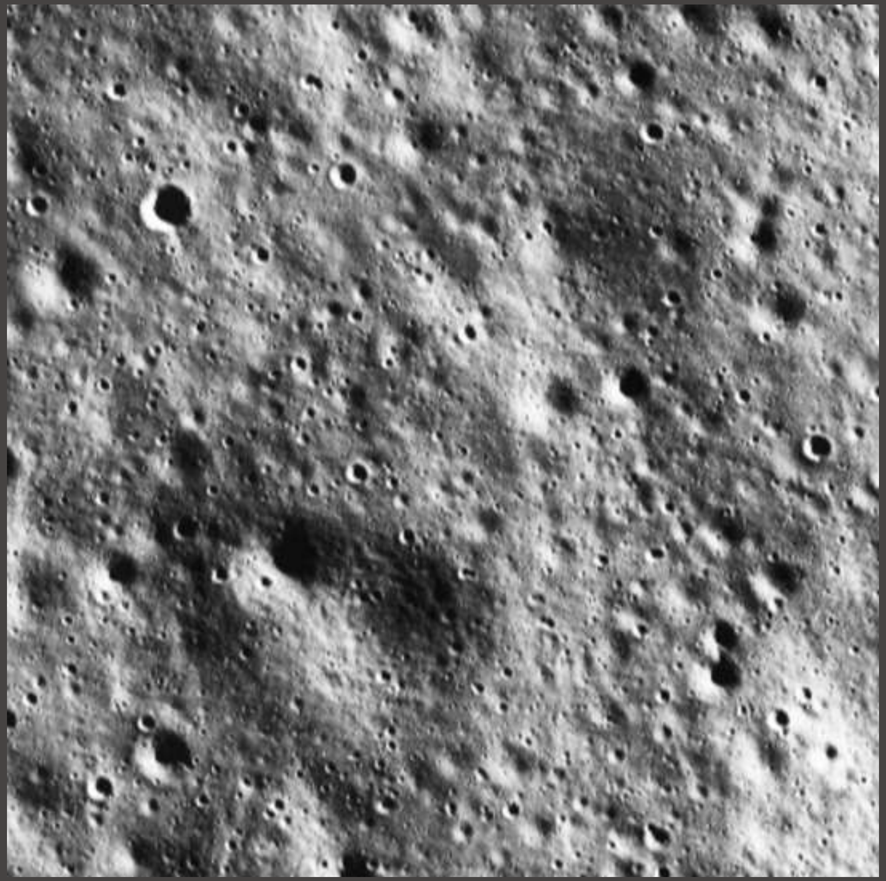
We employ fine-tuned generative models, such as generative adversarial networks (GANs), to enhance the resolution, sharpness of lunar images. These models help us extract valuable information for navigation and analysis.

OpenCV

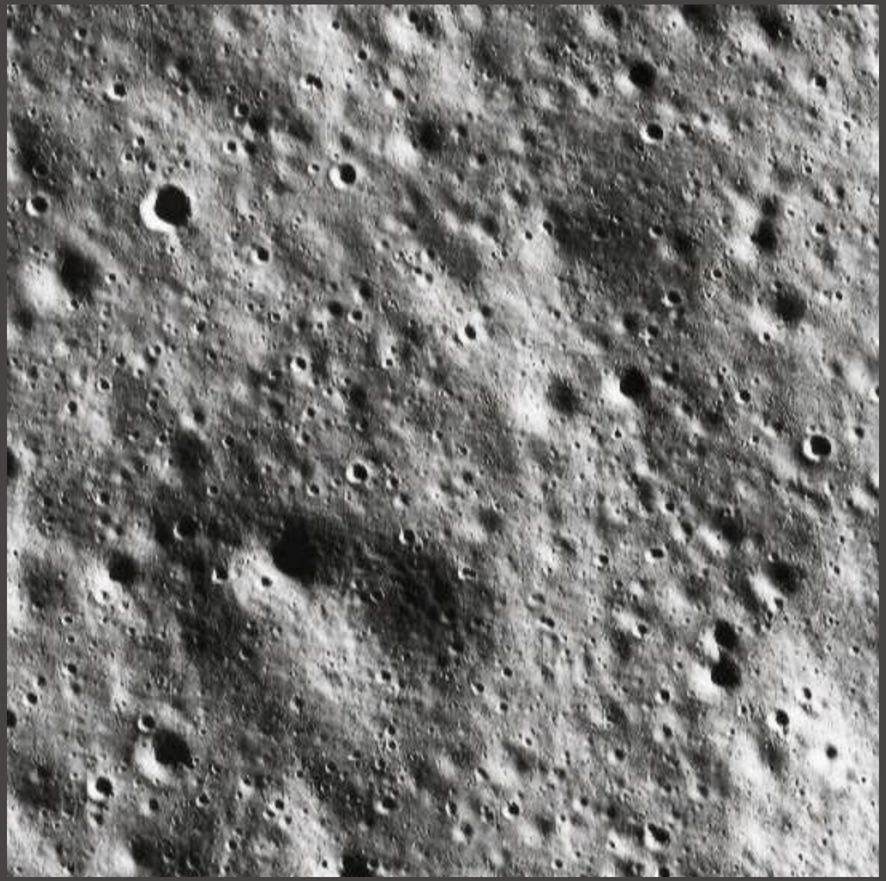
OpenCV is a versatile computer vision library widely used for image and video processing. It provides a seamless interface for utilizing pre-trained models, facilitating tasks such as object detection, face recognition, and image classification.

Result and analysis

Image Super Resolution



Input



Output

Result and analysis

Crater Detection

Input

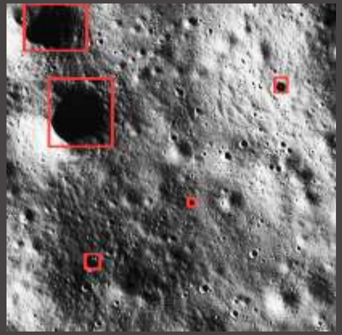
Sample 1

Sample 2

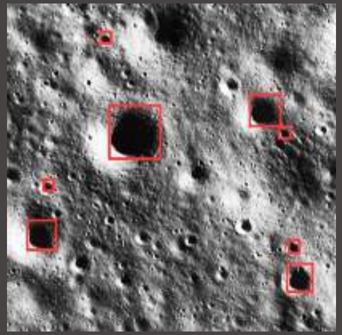
Sample 3

Sample 4

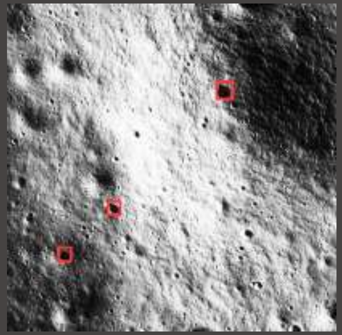
Output



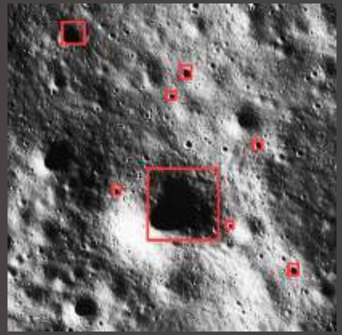
Result 1



Result 2

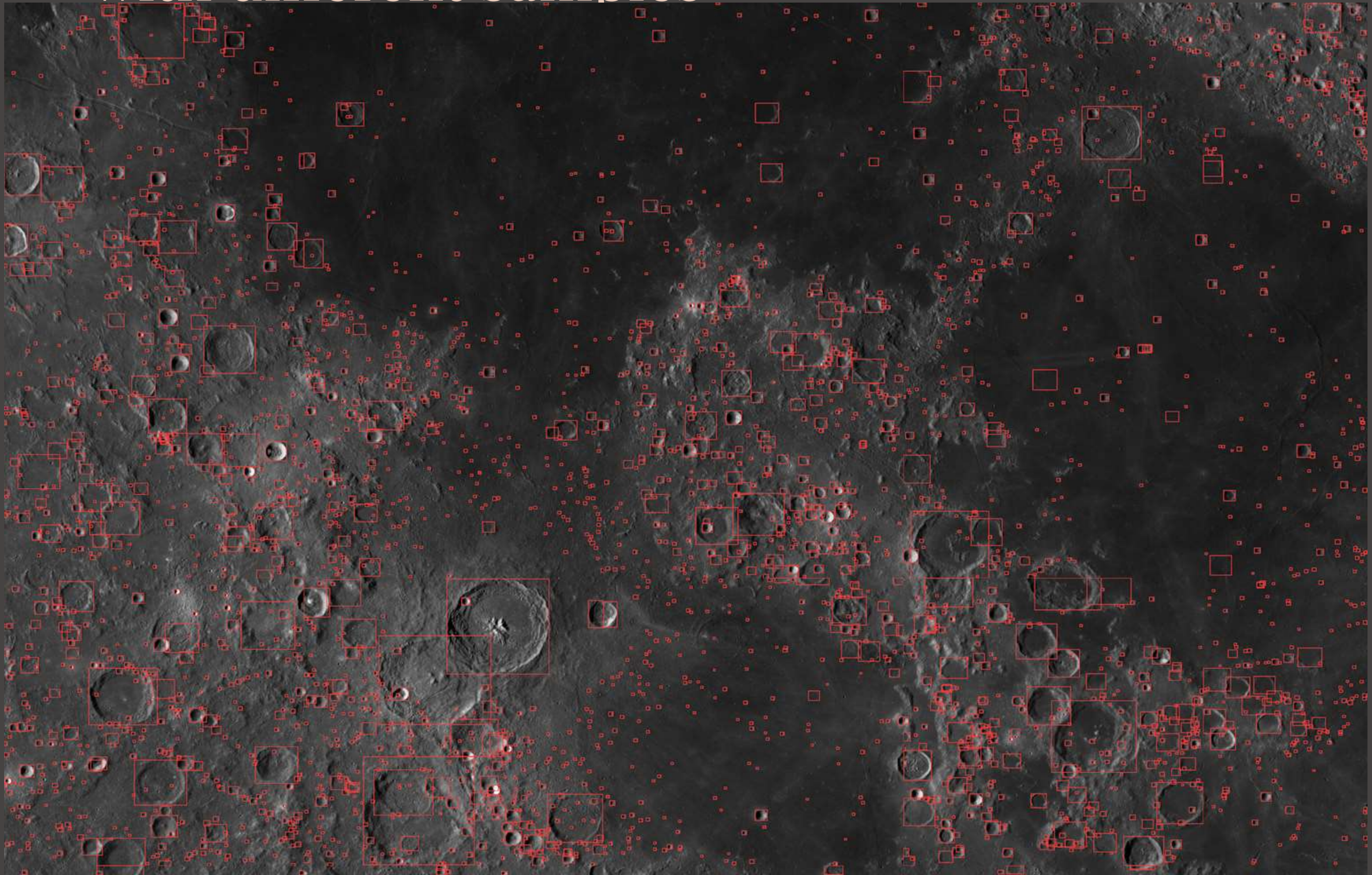


Result 3

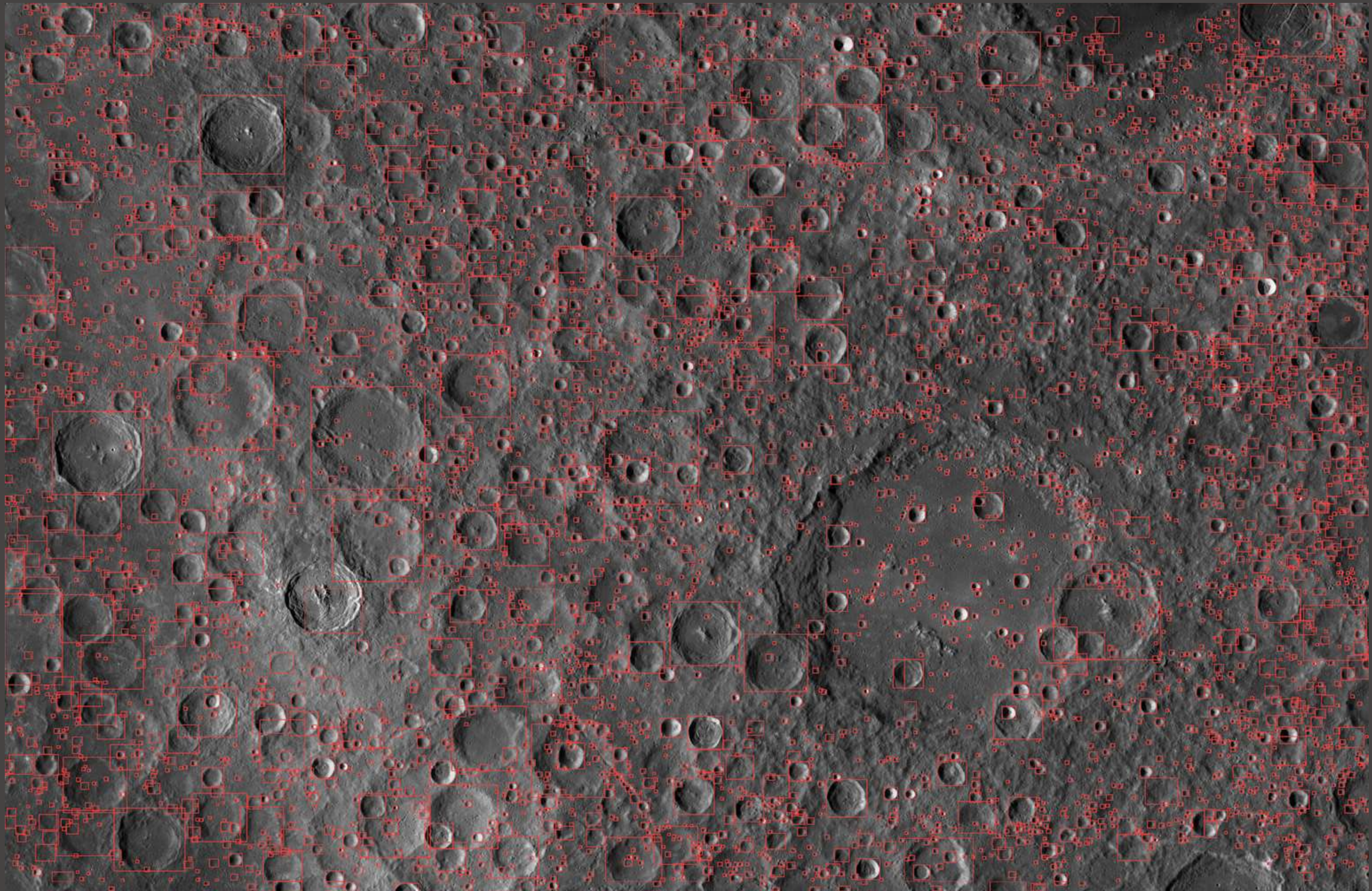


Result 4

Overall Result after training the model with different samples



Overall Result after training the model with different samples



Advancing Lunar Exploration

1

Safe and Precise Lunar Landings

By combining cutting-edge technology and innovative methods, our lunar navigation system ensures safe and precise landings on the moon's surface. This is crucial for future lunar exploration missions.

2

Facilitating Scientific Endeavors

Accurate lunar navigation opens up opportunities for scientific research and exploration. By enabling reliable and efficient navigation, we empower scientists to conduct experiments and collect valuable data.

Chandrayaan-2 PDS4 Data Archive

PDS4 is the de facto international standard for long term archival of planetary science data. For all the scientific payloads, PDS4 data products types [1] were identified and shown in the below

		PDS4 Data Products Types		
Sr. No.	Instruments	Raw	Calibrated	Derived
1	TMC2	Yes	Yes	Yes
2	IIRS	Yes	Yes	Yes
3	OHRC	Yes	Yes	No
4	SAR	Yes	Yes	No
5	CLASS	Yes	No	No
6	XSM	Yes	Yes	No
7	CHACE-2	Yes	No	No

Chandrayaan-2 PDS4 Data Archive

PDS4 Level	PDS4 Level Description	ISRO Level	CODMAC Level
Raw	Original data from an instrument after initial pre-processing like decompression, reformatting, packetization etc.. the archived data are in a PDS approved archive format.	0	2
Calibrated	Data converted to physical units, which makes values independent of the instrument (Radiometrically corrected & seleno-tagged)	1	3
Derived	Results that have been distilled from one or more calibrated data products (for example, maps, gravity or magnetic fields, or ring particle size distributions). Supplementary data, such as calibration tables or tables of viewing geometry, used to interpret observational data should also be classified as 'derived' data if not easily matched to one of the other three categories (higher level products like ortho, DEM)	2	4+

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TMC2 PDS4 Data Products

The PDS4 Data Products for TMC2 is defined based on the defined data processing levels (L0, L1 and L2) as Raw, Calibrated and Derived data products.

- Raw Data Products: Raw Data Products contains raw data without any correction along with the system level corner coordinates. For each payload observation, PDS4 data products are generated (based on product id & sensor id derived from file name, zipped and organized under year month day wise collection directory defined under instrument collection structure

  For example, user has downloaded the zip product as:
  - ch2_tmc_nrf_20191015T102125157610840_d_img_blr.zip
  - ch2_tmc_nra_20191015T102125154360840_d_img_blr.zip
  - ch2_tmc_nrn_20191015T102125154360840_d_img_blr.zip

- Calibrated Data Products: Calibrated Data Products contains radiometrically corrected data along with the refined corner coordinates. For each payload observation, PDS4 data products are generated (based on product id derived from file name, zipped and organized under year month day wise collection directory defined under instrument collection structure.

  For example, user has to download the zip product as:
  - ch2_tmc_ncf_20191015T102125157610840_d_img_blr.zip
  - ch2_tmc_nca_20191015T102125154360840_d_img_blr.zip
  - ch2_tmc_ncn_20191015T102125154360840_d_img_blr.zip

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TMC2 PDS4 Data Products

- Derived Data Products:: Derived Data Products contains radiometrically and geometrically corrected data along with the corner coordinates. For each payload observation, PDS4 data products are generated (based on product id derived from file name,, zipped and organized under year month day wise collection directory defined under instrument collection structure
  For example, user has downloaded the zip product as:
    - ch2_tmc_ndn_20191015T102125154360840_d_dtm_blr.zip
    - ch2_tmc_ndn_20191015T102125154360840_d_oth_blr.zip

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TMC2 PDS4 Archive Products

Data that comprises the TMC 2 archives are formatted in accordance with PDS specifications. This section provides details on the formats used for each of the products included in the archive

- TMC 2 instrument is an imaging payload. The primary data collected from instrument is raw image. The TMC 2 imager has three sensors – Fore, Aft and Nadir. For each sensor both primary as well as secondary data sets are defined that contains data product levels, types and formats shown in the table:

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TMC2 PDS4 Archive Products

Sensors	PDS4 Data Product Levels	PDS4 Data Products Types	Data Formats	Data type*
For each sensor - Fore, Aft and Nadir	Raw	Image	Binary	UnsignedLSB2
	Raw	Browse	PNG	UnsignedByte
	Calibrated	Image	Binary	UnsignedLSB2
	Calibrated	Browse	PNG	UnsignedByte
	Calibrated	Geometry	CSV	ASCII Text
Stereo / Triplet Combination	Derived	DEM	Geo Tiff	SignedLSB2 (Float/ double)
	Derived	Ortho	Geo Tiff	UnsignedLSB2
	Derived	Browse DEM	PNG	UnsignedByte
	Derived	Browse Ortho	PNG	UnsignedByte

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DTM

Digital Elevation Model (DEM), Digital Surface Model (DSM) and Digital Terrain Model (DTM) are three commonly implemented geospatial features generated with UAV mapping systems. Each data product delivers different elevation values as each model uses different methodologies. Elevation values from a LiDAR point cloud come from features including bare-ground, power lines, tree canopies or buildings.

A **DTM** (Digital Terrain Model) typically augments a DEM, by including vector features of the natural terrain, such as rivers and ridges. A DTM may be interpolated to generate a DEM, but not vice versa.

A DTM usually contains all the depth information of the map and is very useful for conveying the topography of a land sector.

A DTM is usually used in conjunction with a GIS (geographic information system) which can render the data in these images with various useful renders.

QGIS

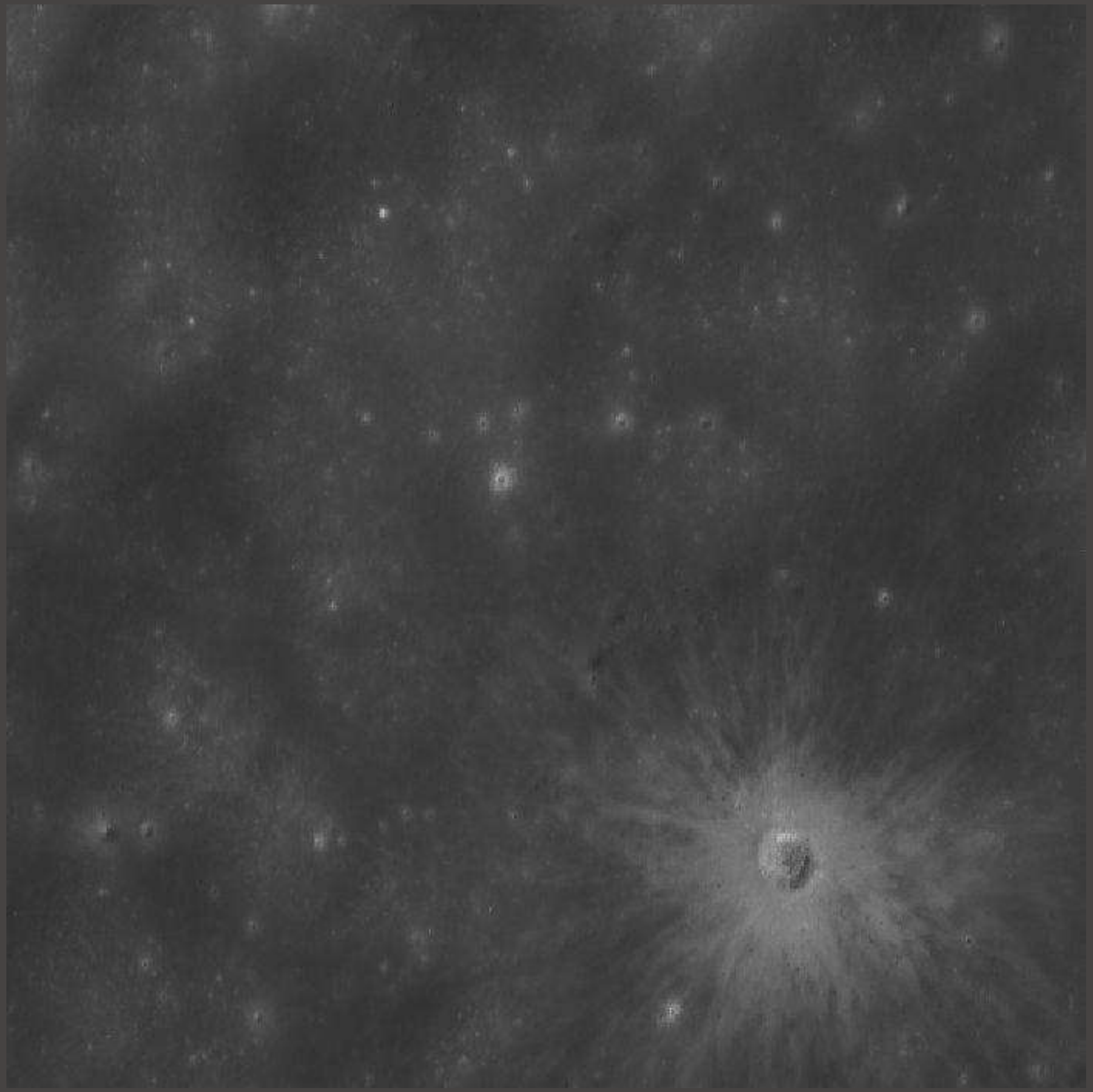

Fig: Oth image of the moon

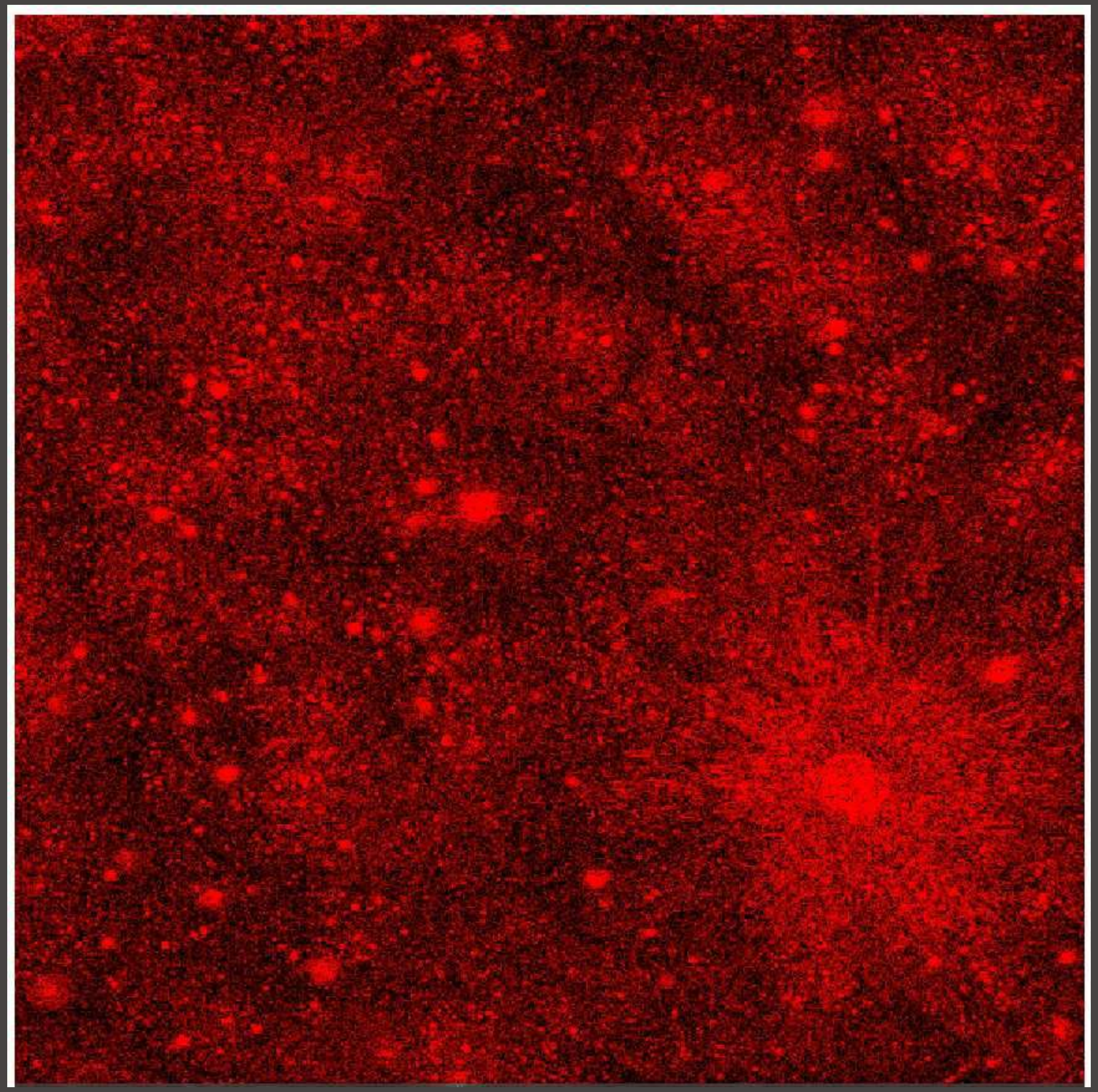

Fig: Generated the slope map of the given Oth with set parameter of slope greater than 10 deg, to be illustrated in red

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QGIS

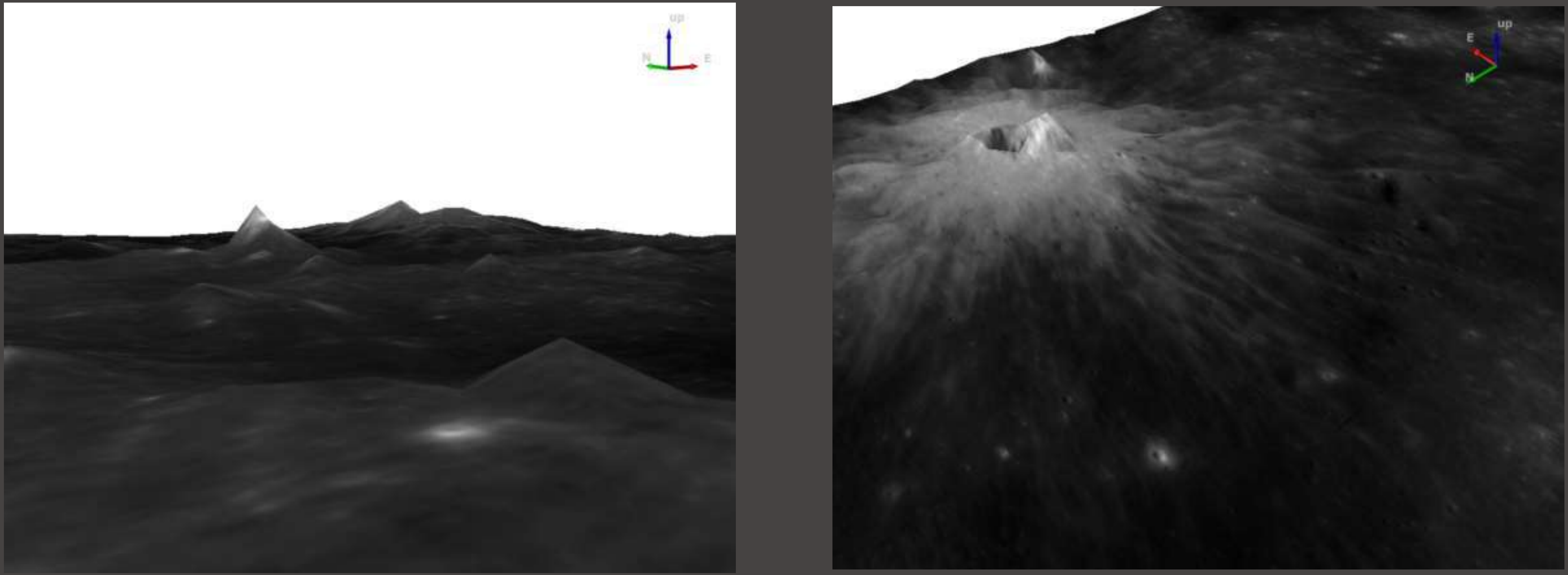

Fig: A 3-D Surface render made by QGIS of the same scene

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Slope Map

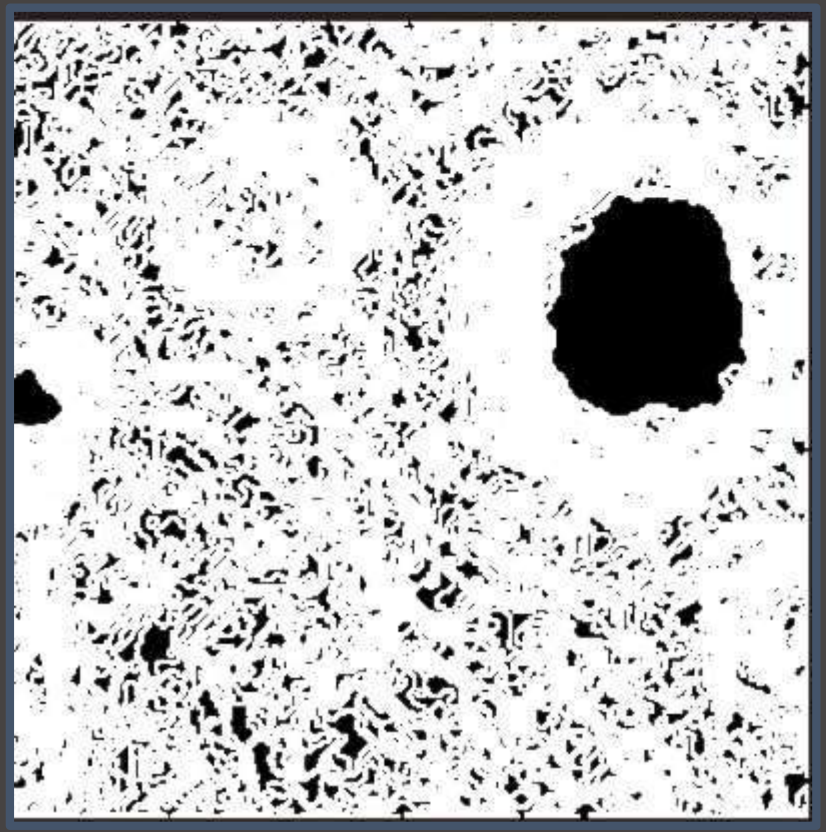

Fig: Slope Map of a given DMT

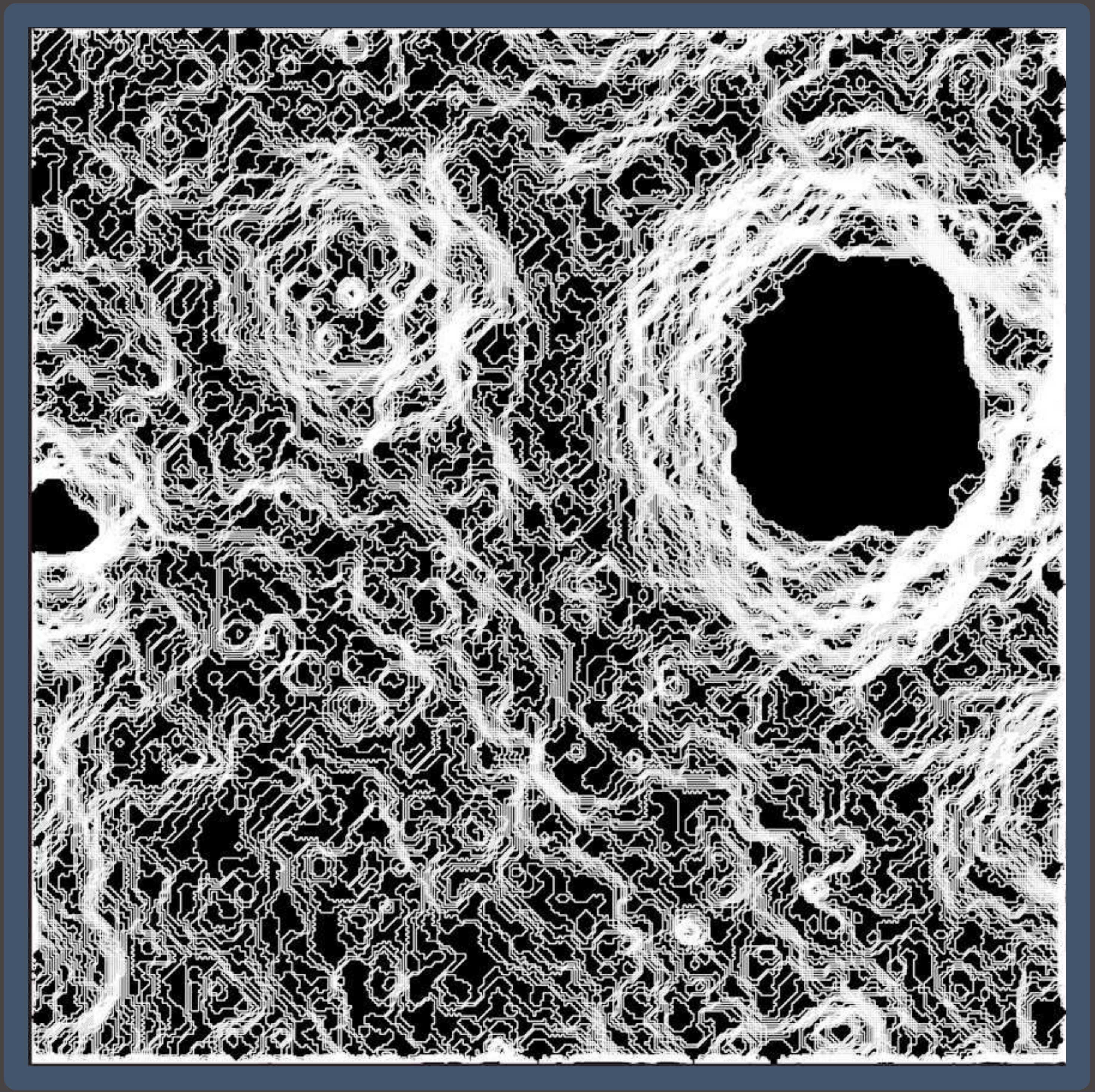

Fig: Slope map of Super Sampled DMT

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Slope Hazard

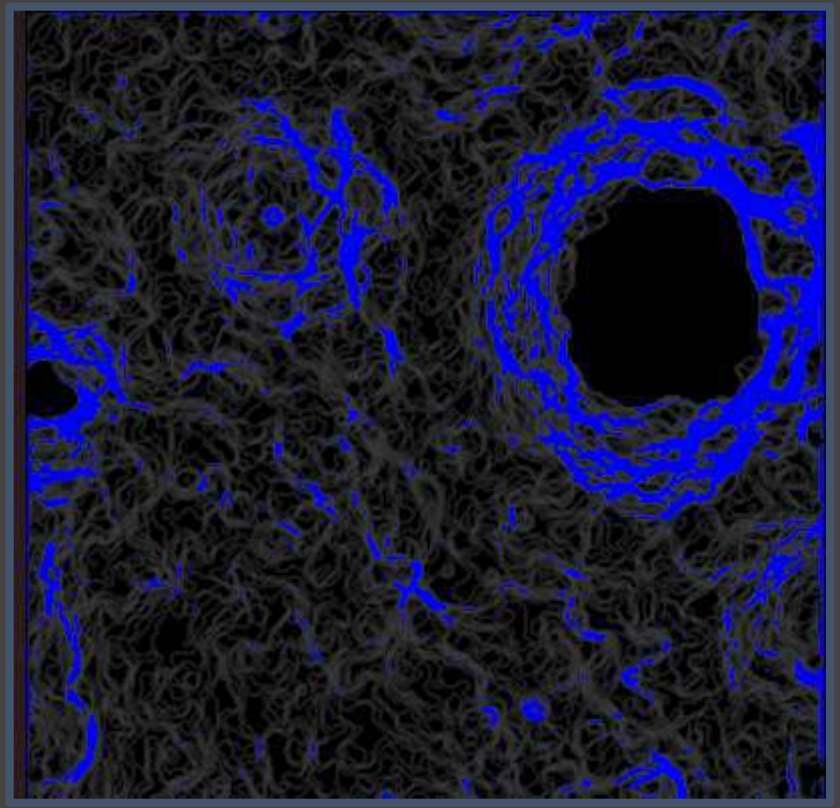

Fig: Slope Hazard Map (indicates points with slope greater than 10deg)

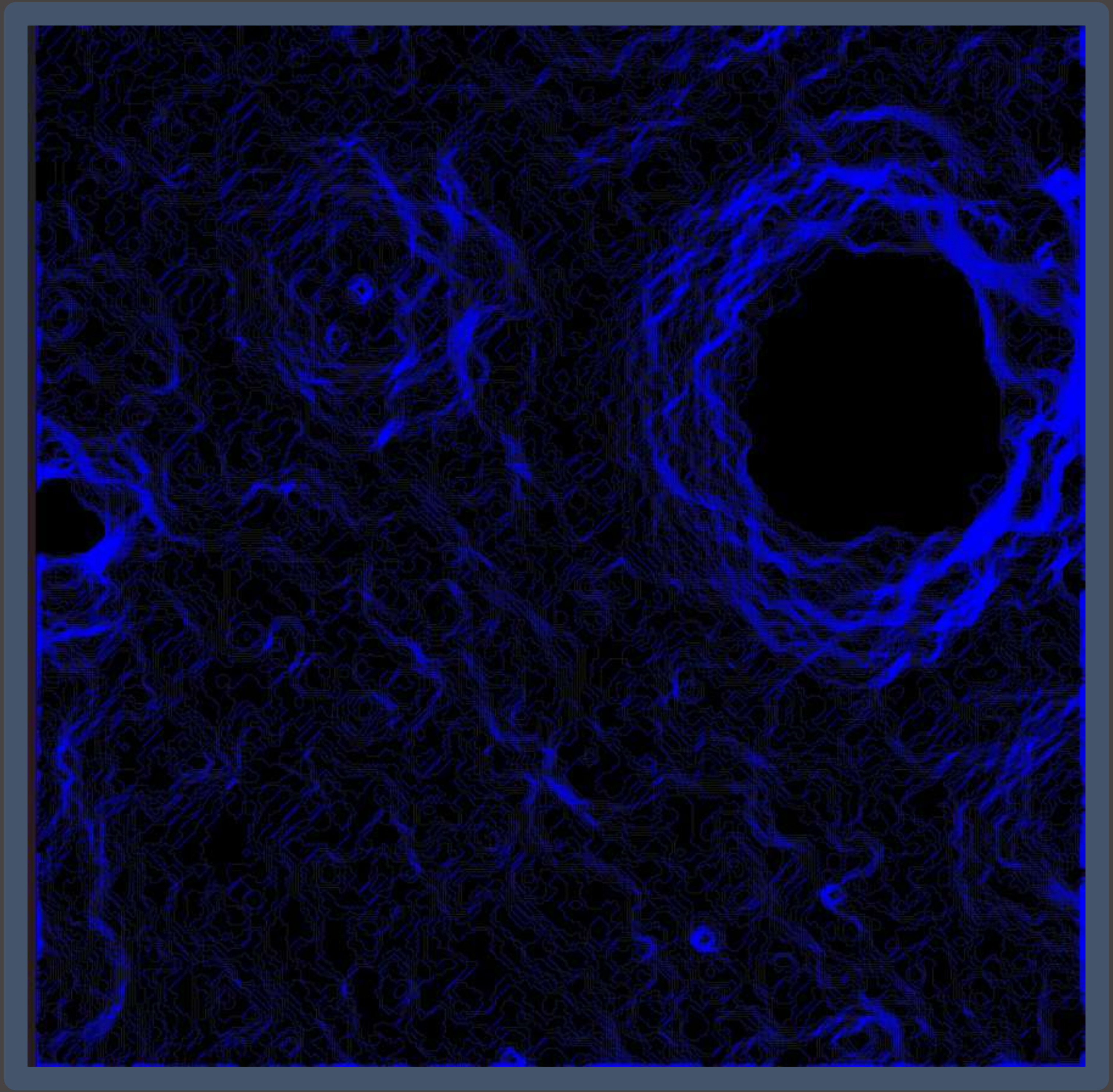

Fig: Slope Hazard Map for super sampled DMT

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Crater Detection

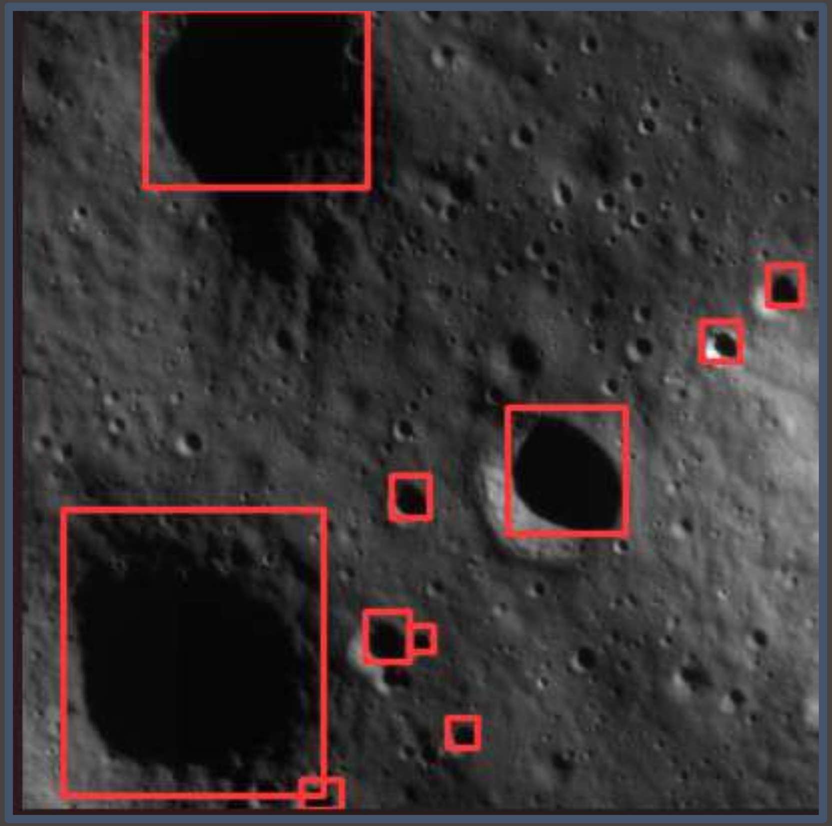

Fig: Crater Detection with Ellipse RCNN model

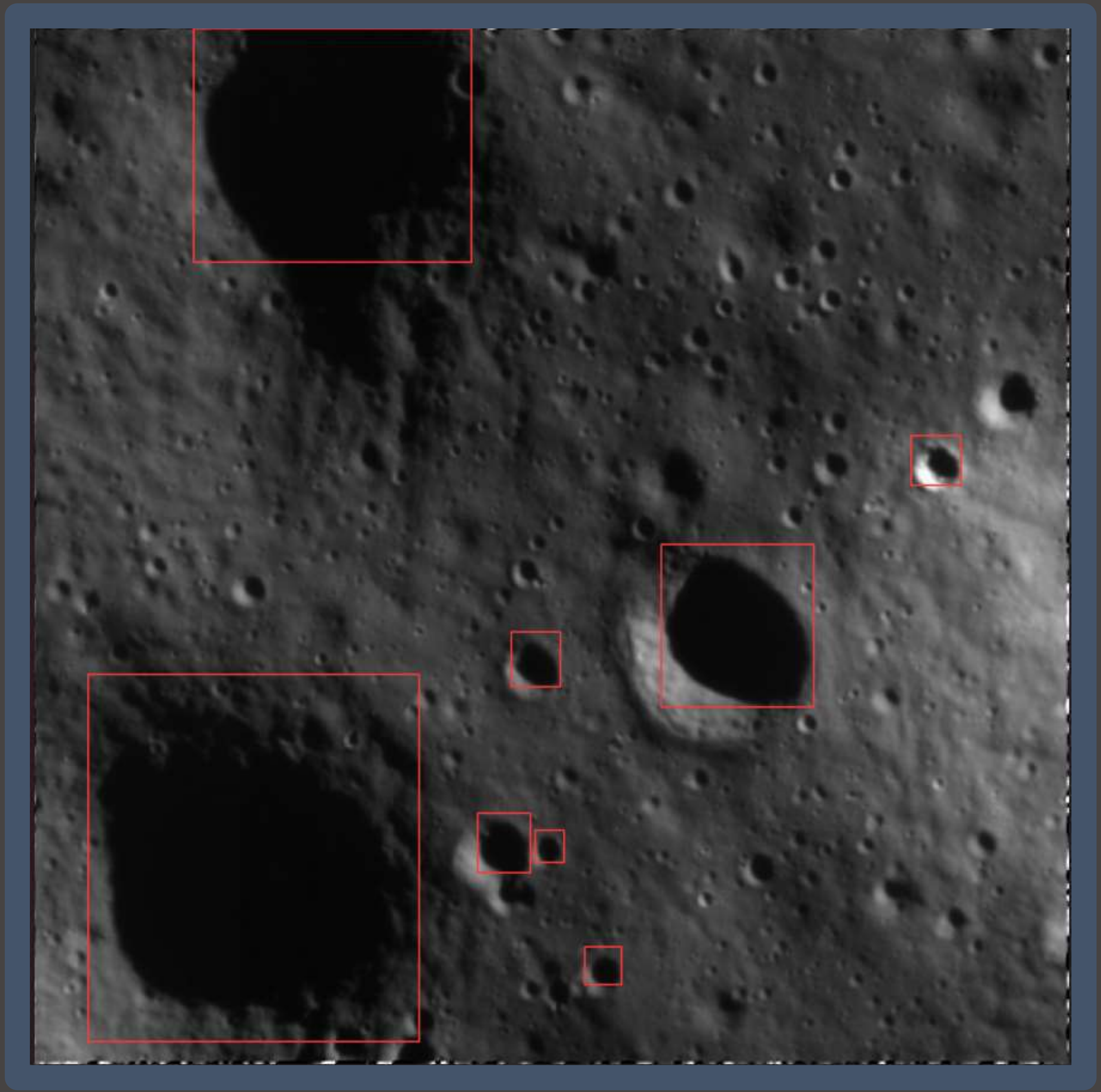

Fig: Crater detection of Super Samled Image

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Shadow Detection

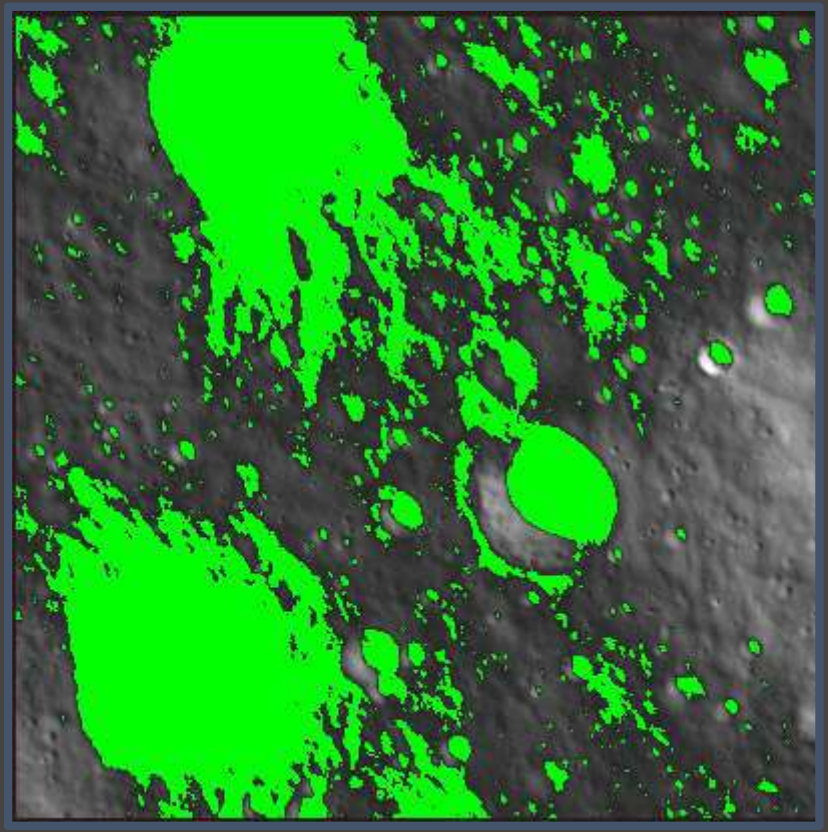

Fig: Shadow Detection on surface with help of Orthographic images

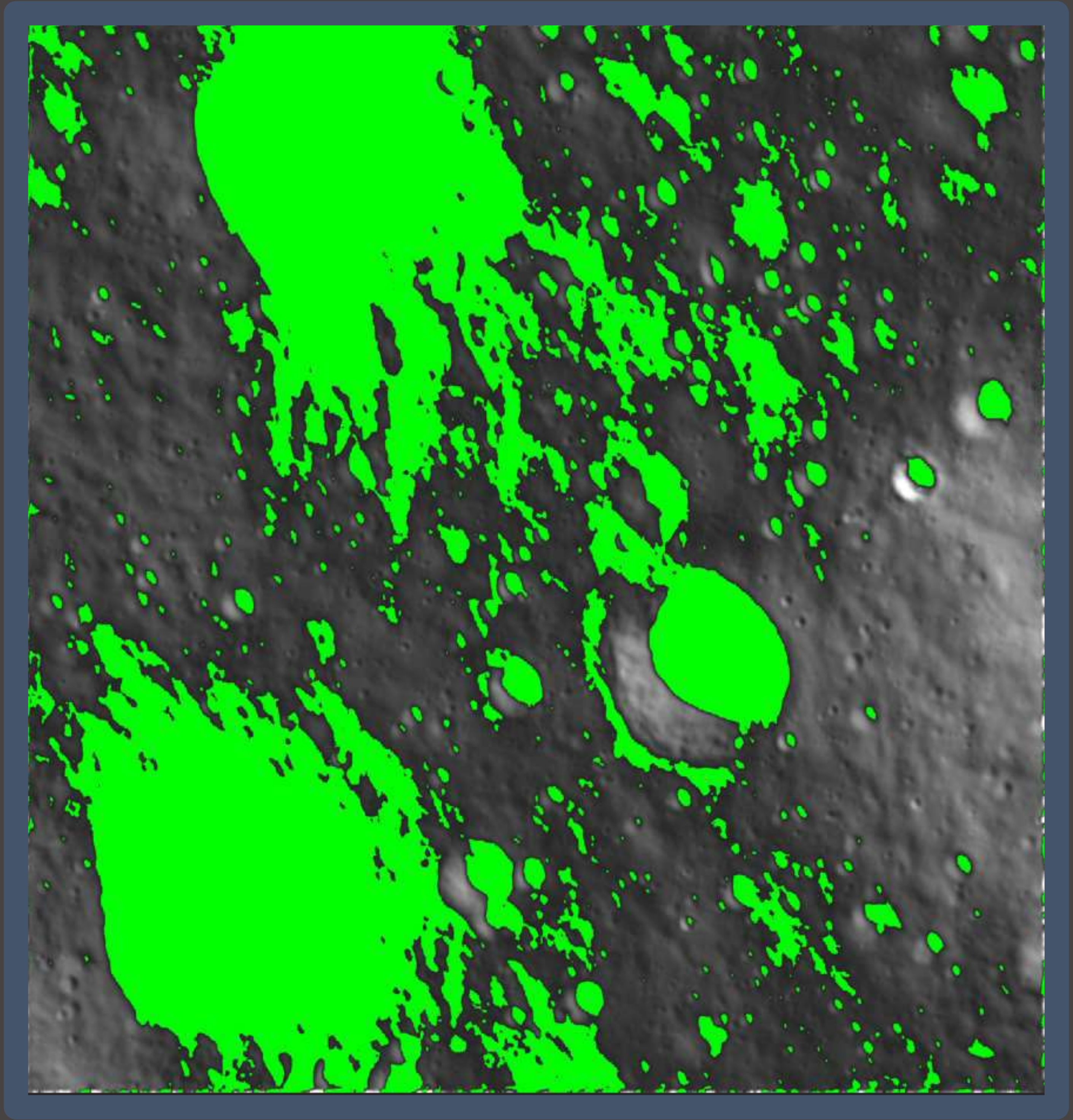

Fig: Shadow detection on Super Sampled Image

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Hazard Map Detection

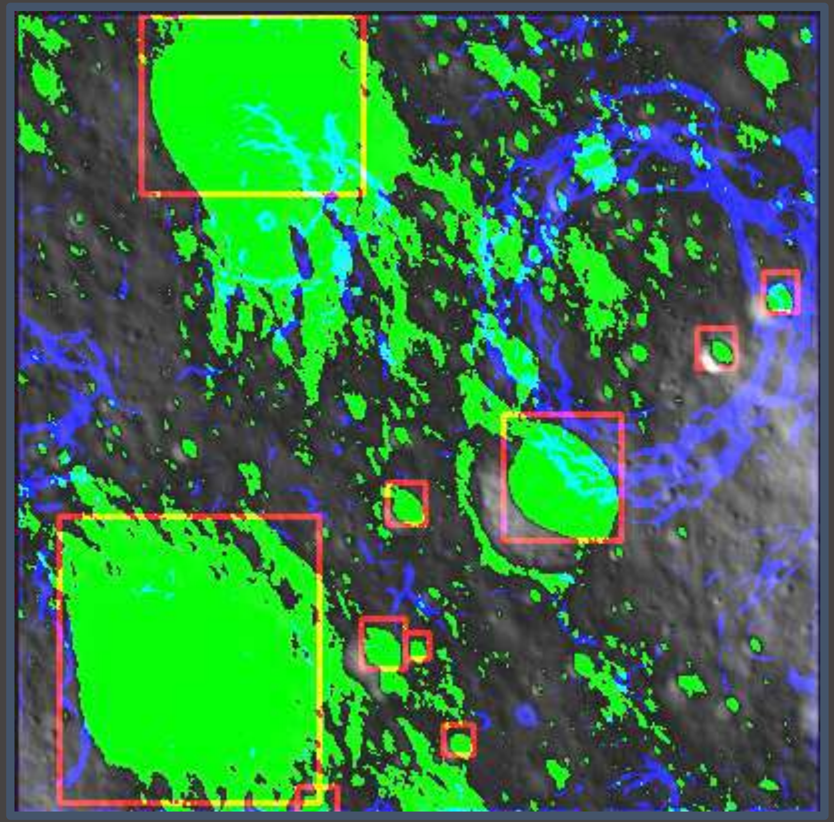

Fig: Hazard Map indicating craters, boulders, shadows and high inclinations

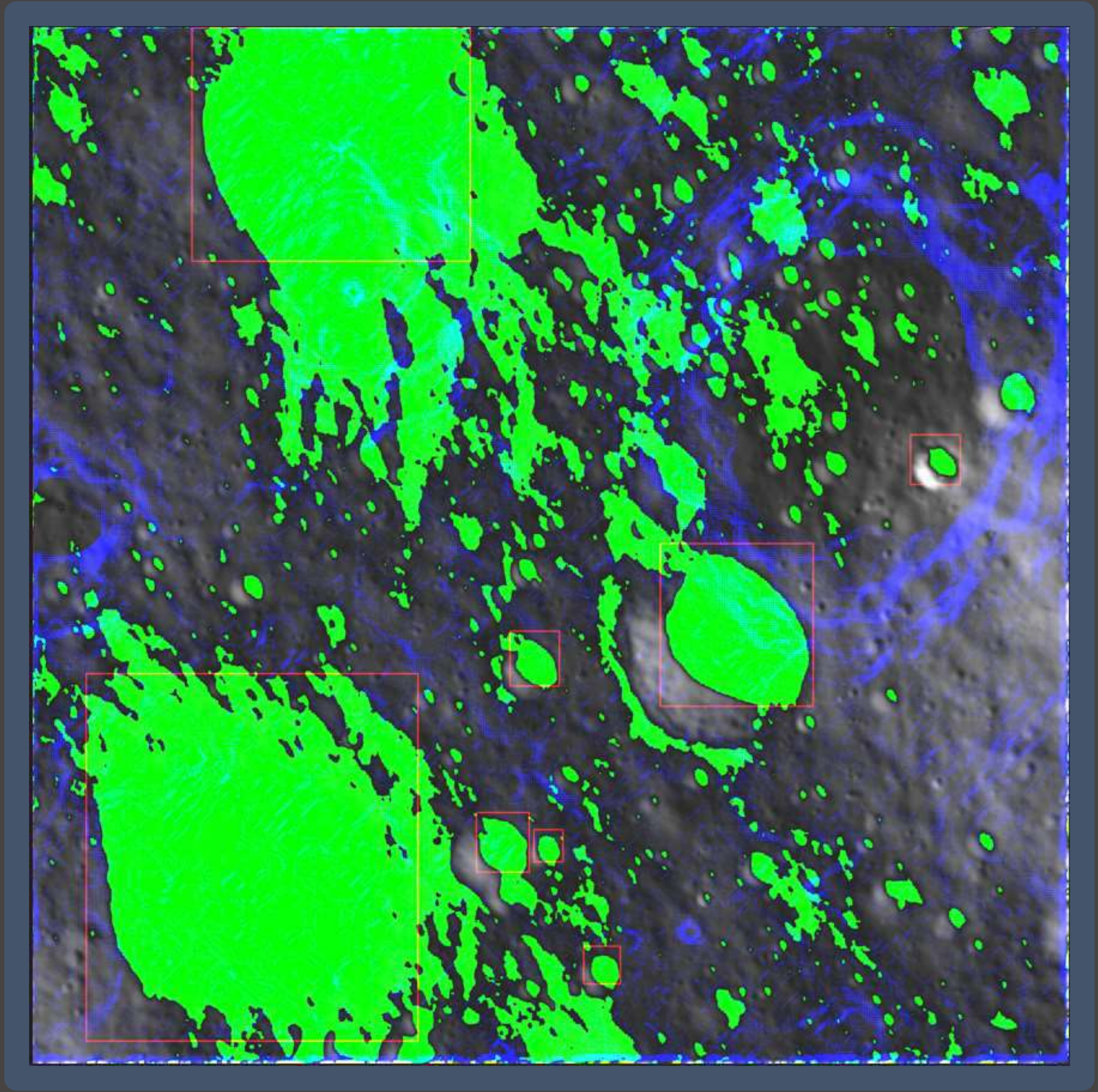

Fig: Hazard map on SuperSampled image

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Creation of Hazard Map

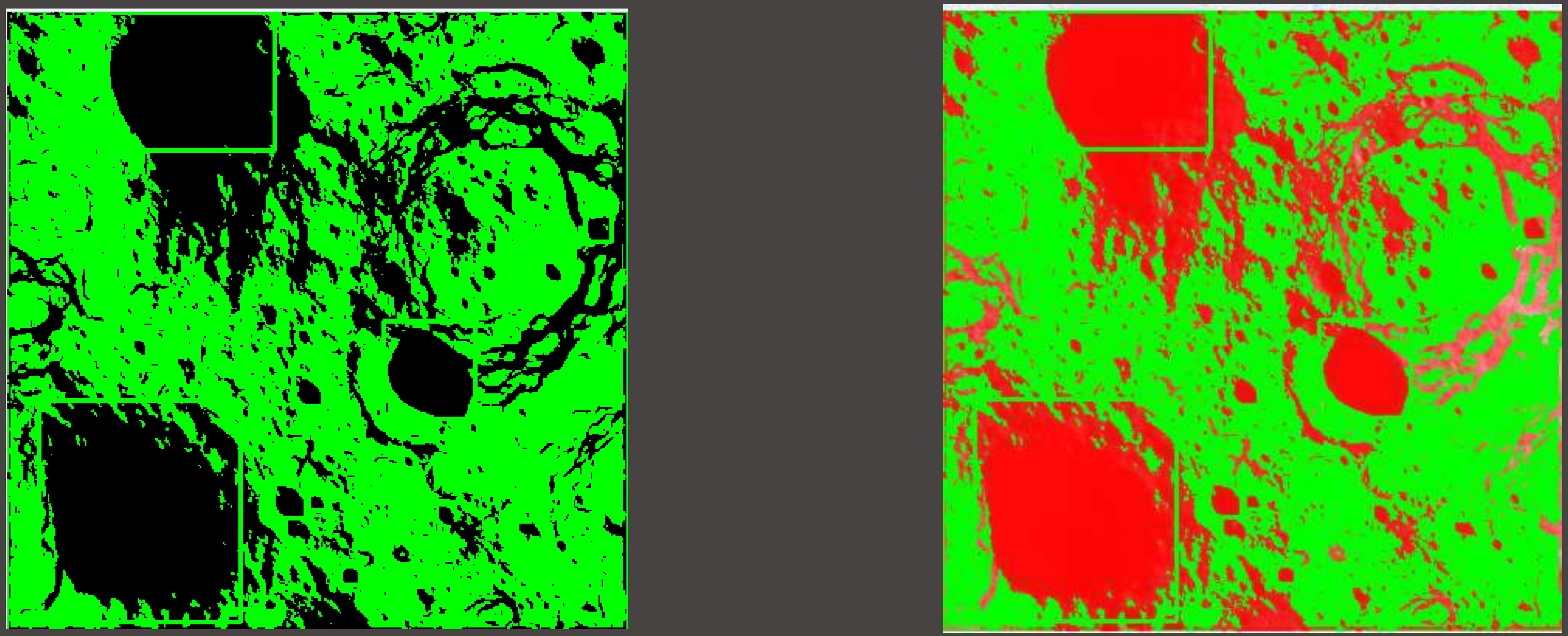

Fig: Final Hazard Map

Thank You