Team Name: **Quadrupole**
Name of College(s)/University(s): **Department of Physics, Indian Institute of Science, Bangalore**

Team Members Details:

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Problem Statement: Automatic detection of craters & boulders from Orbiter High Resolution Camera(OHRC) images using AI/ML techniques

Detailed solution and Approach

Our objective is to **maximize crater and boulder detection** on the lunar surface using Chandrayaan-2's Orbiter High-Resolution Camera (OHRC) imagery. We have **manually labelled OHRC images**, identifying center coordinates, height, and width of bounding boxes of craters and boulders. This identification relies on shadows and sun direction, with darker and brighter regions present for features opposite the sun's direction. Boulders protrude from the surface, casting shadows and often appearing in clusters, while craters exhibit smoother floors compared to surrounding terrain.

Initially, we employed YOLO and Faster R-CNN for object detection. However, these methods yielded low confidence (<50%) in detecting craters and identified very few boulders. To address this, **we have developed an innovative solution combining YOLO with SAHI (Slicing Array Hyper Interference)**. Our approach first **divides each large OHRC image (~7500x1200 px) into approximately 24 smaller (640x640 px) images** to enhance accuracy. We then **label these images for craters and boulders using Roboflow.**

Our two-stage detection process begins by **training YOLO on these smaller images** to improve upon the pre-trained model. Subsequently, **we apply SAHI to detect even smaller objects within our images**. This combined YOLO+SAHI approach significantly improves detection capabilities with high confidence (>50%), as demonstrated in our qualitative estimation shown in subsequent slides. After training YOLO, SAHI can be applied directly to the large original images for comprehensive detection.

Furthermore, we utilize the grid.csv file provided with OHRC images and the normalized labels generated from test data to **quantify the selenographic position** of each detected craters and boulders and hence determining the radius of the craters and boulders.

Tools and Technology Used

- **Roboflow** for labelling the data
- **OpenCV** and **Pillow** for loading and preprocessing the images
- **Wandb** used for post training data analytics (Losses, Accuracy, etc.)
- **R-CNN**, based on **TensorFlow Object Detection API** (Alternate Model)
- **YOLO**, based on **Ultralytics**, used for fine-tuning
- **SAHI**, used for refining the detection in the image

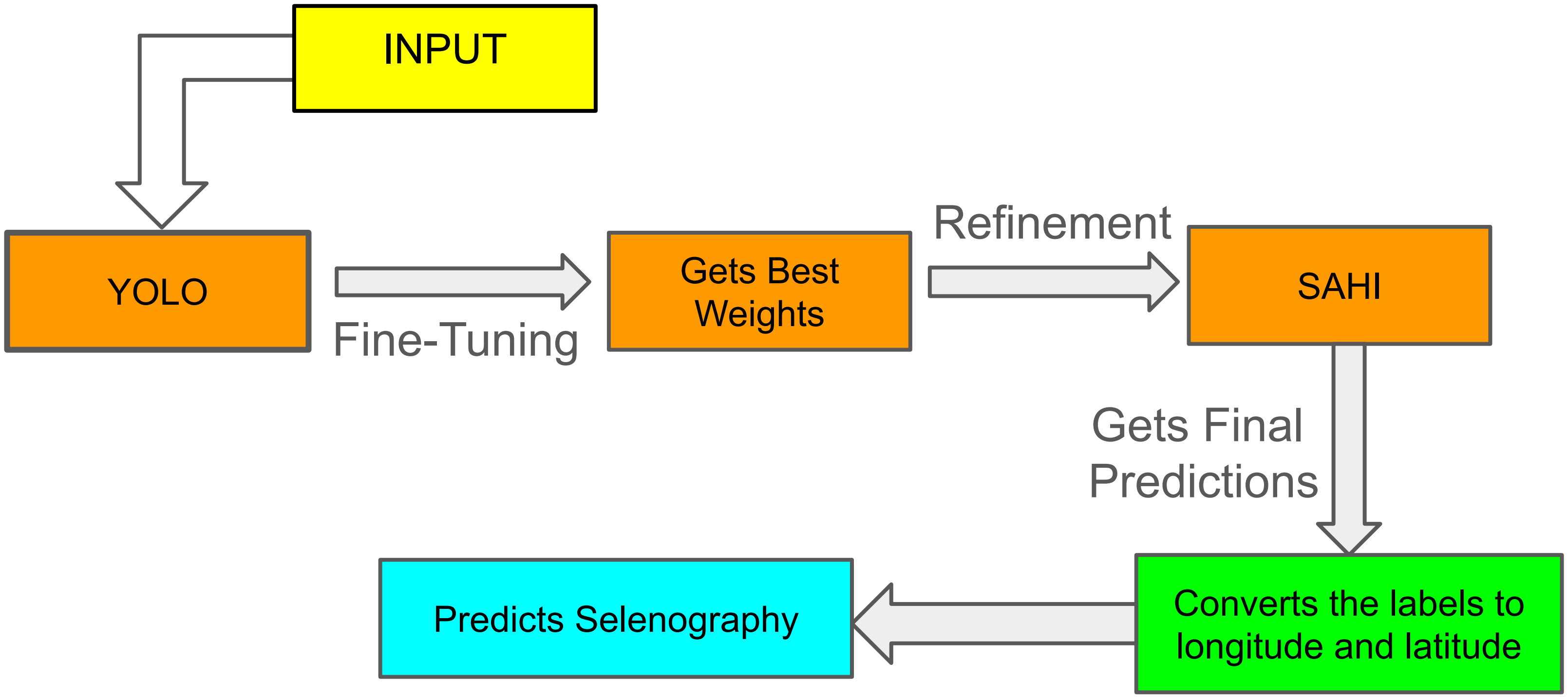
- How different is it from any of the other existing ideas?
- How will it be able to solve the problem?
- USP of the proposed solution

People have worked on various ideas to detect craters and boulders separately and different architecture exist in literature to solve the problem. Our approach is innovative in several key aspects:

- **Dual-purpose detection**: Our method performs equally well for both craters and boulders, eliminating the need for separate detection systems.
- **Enhanced small object detection**: The system can identify even smaller craters and boulders, improving overall detection accuracy.
- **Flexible image processing**: Our approach works efficiently on larger images, regardless of their shape, size and resolution.
- **Advanced combined model**: We utilize a YOLO+SAHI architecture, which:
  - Systematically scans the image using sliding windows.
  - Detects objects of various sizes within these subregions.
  - Integrates results for comprehensive detection across the entire image.

A visual representation of this process is provided in the accompanying visualization slide

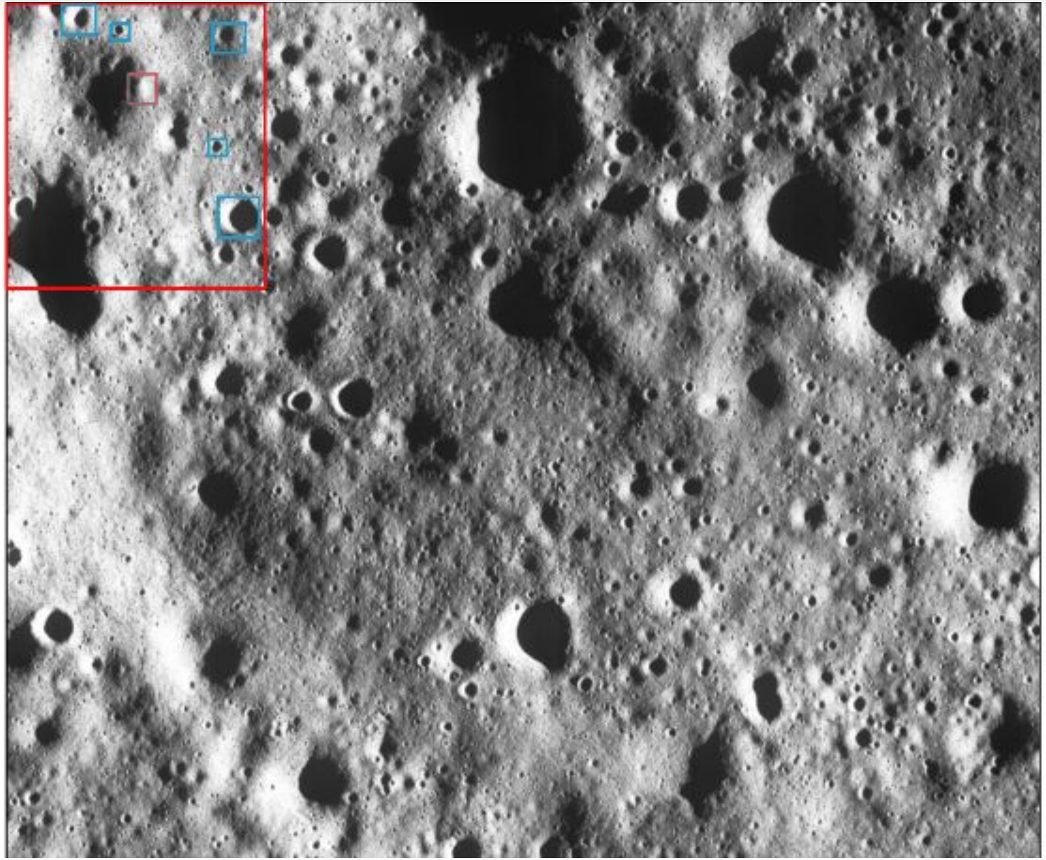
Proposed architecture/user diagram



List of features offered by the solution

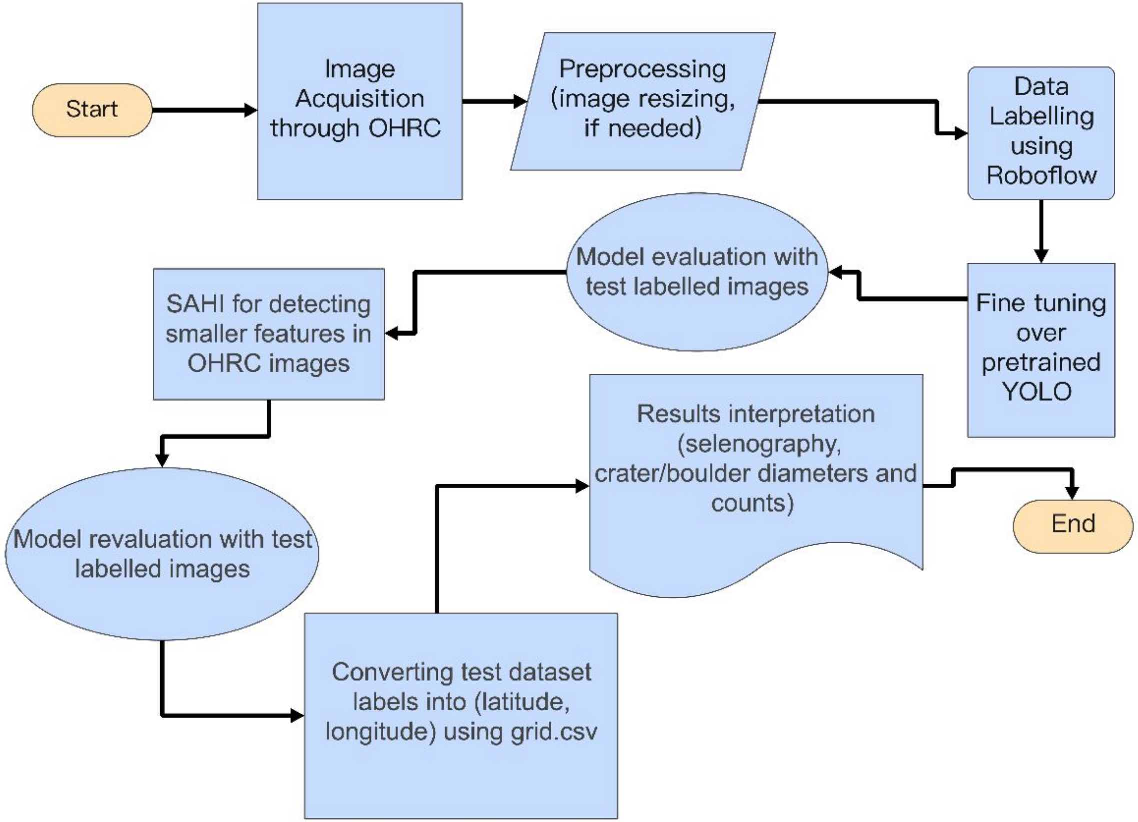
SAHI is capable of small object detection and inference.

- A fixed size rectangle slides across the image which then performs classification task in each window.
- Craters (Blue box) and Boulders (Purple box) are detected from larger resized versions of these windows.
- Key Features of SAHI includes **resource efficiency** (Optimized memory usage and high quality detection on limited resources), **preserves detection quality** and **enhanced scalability** (Detection on different size and resolution of images).



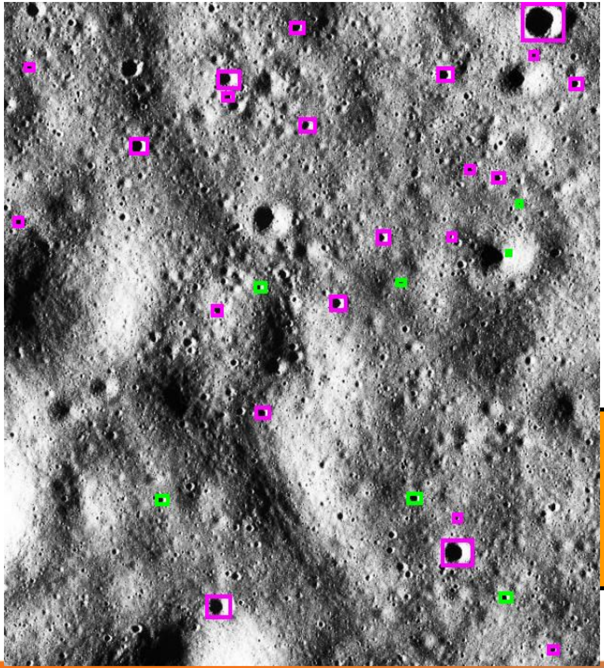
This GIF is just for illustration

Process flow diagram or Use-case diagram



Wireframes/Mock diagrams of the proposed solution

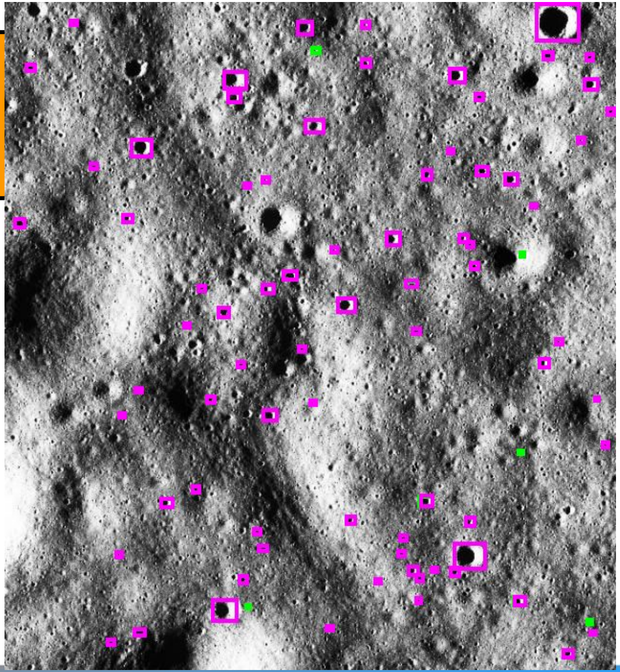
We are comparing different models being deployed in our proposed solution comparing test images after training the sample vs actual test data for mock clarification of USP of our model. **Further, for illustration purpose, we take a larger sliding rectangle in SAHI refinement.** The model can detect much larger number of craters (purple box) and boulders (green box) depending upon the rectangle size used in SAHI.



YOLO+ SAHI: Detections: 89

Prediction on 1/24th of OHRC dataset

Only YOLO: Detections: 30



Solution Brief (Overall)

- Our approach involves **manually labelling data** based on shadows and sun direction, with longer shadows indicating taller features or steeper slopes.

- Initially, YOLO and Faster R-CNN were used for detection but yielded low confidence results. The improved method **combines YOLO with SAHI**, which excels at detecting even smaller objects with higher confidence in original images.

- The process involves **dividing** large OHRC images into smaller segments, **labelling** them using Roboflow, **training YOLO** on these images, and then **applying SAHI** on original image for more refined detection.

- Additionally, by utilizing the labelled output data and grid.csv file provided with OHRC images, **the system can quantify the selenographic position of detected objects** and hence the **diameter of the detected craters and boulders.**

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Innovation partner H2S

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THANK YOU