Applying Deep Learning for Optical Navigation in Solar System Exploration Missions

PhD Doctoral Meetings 2025
PhD program in Aerospace Engineering UC3M

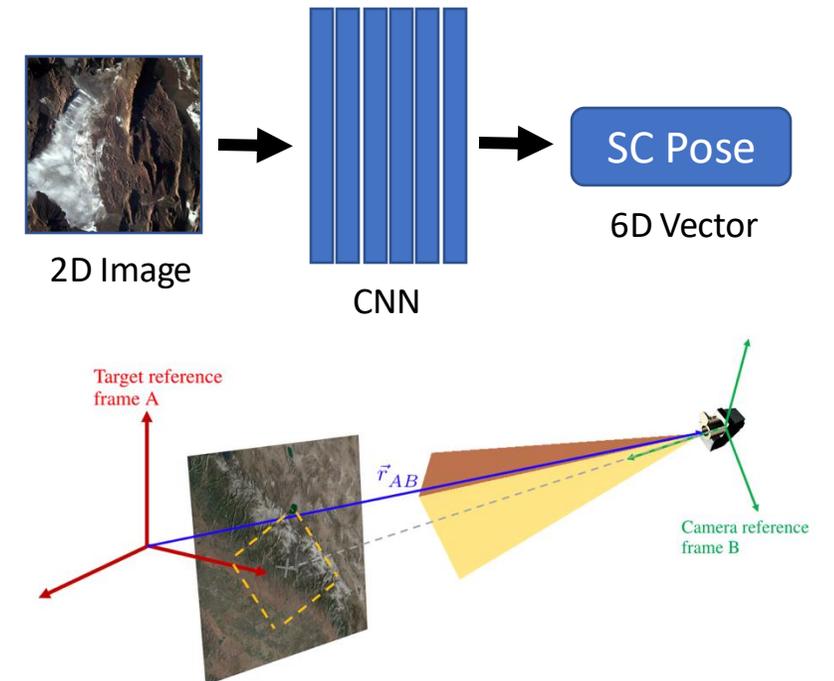**Alfredo Escalante López**
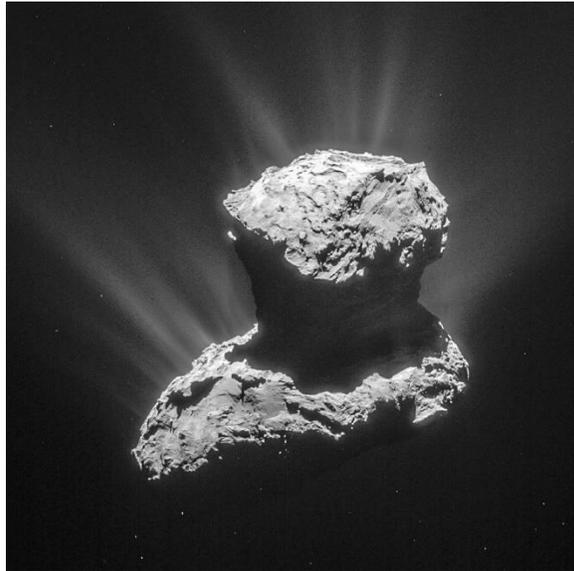
Supervisors:

Manuel Sanjurjo and **Pablo Ghiglino**

Deep Learning for Optical Navigation

- Study the applicability of Convolutional Neural Networks (CNN) for optical relative navigation as a lightweight and robust solution.

- Classical methods are computationally expensive and fail under adverse illumination conditions.

- Training of a Neural Network for directly learning the non-linear transformation between the grayscale image (2D space) to the spacecraft pose vector (6D space)

- Challenges:

  - The CNN would act like a black-box, extensive testing must be done for validation and identification of possible failure cases

  - Machine learning applications require a very-large amount of data for training and testing, but real data sets are very limited
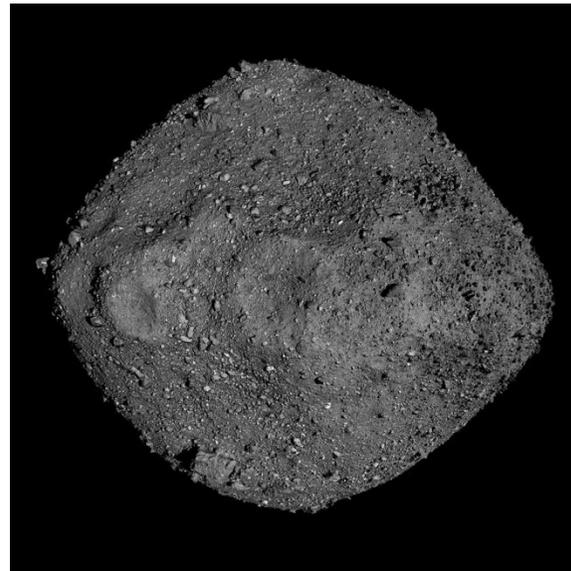
  - Generalization of machine learning solution

2D Image → CNN → SC Pose (6D Vector)

Target reference frame A

$\vec{r}_{AB}$

Camera reference frame B

Orbiter Missions Use Cases

Comet 67P

- Dominated by topography

- Dust and particles ejected

- Whole target in FoV

Bennu

- Very rocky surface

- Dominated by topography and albedo

- Whole target in FoV

Moon

- Dominated by topography and albedo

- Large shadows at polar regions
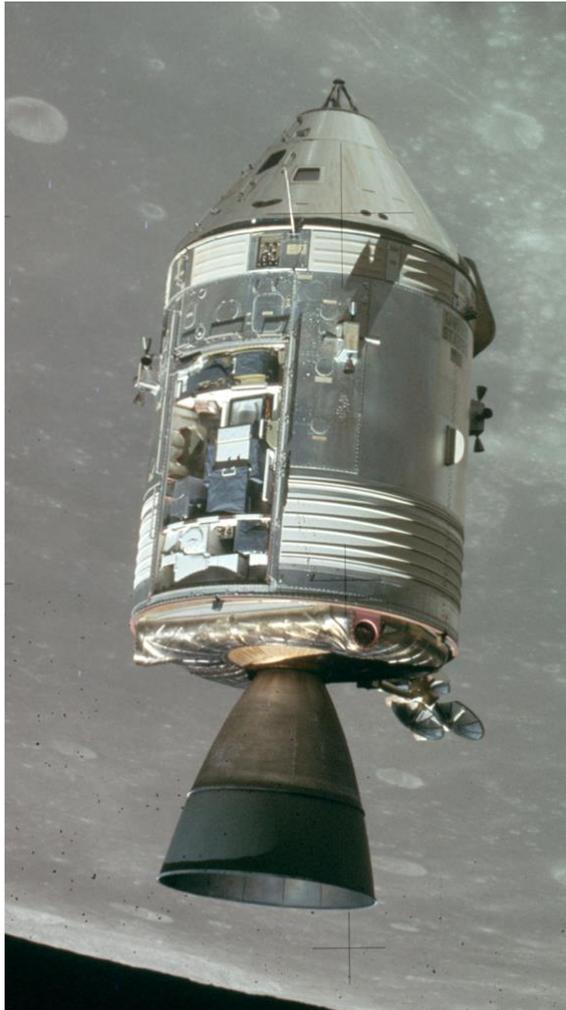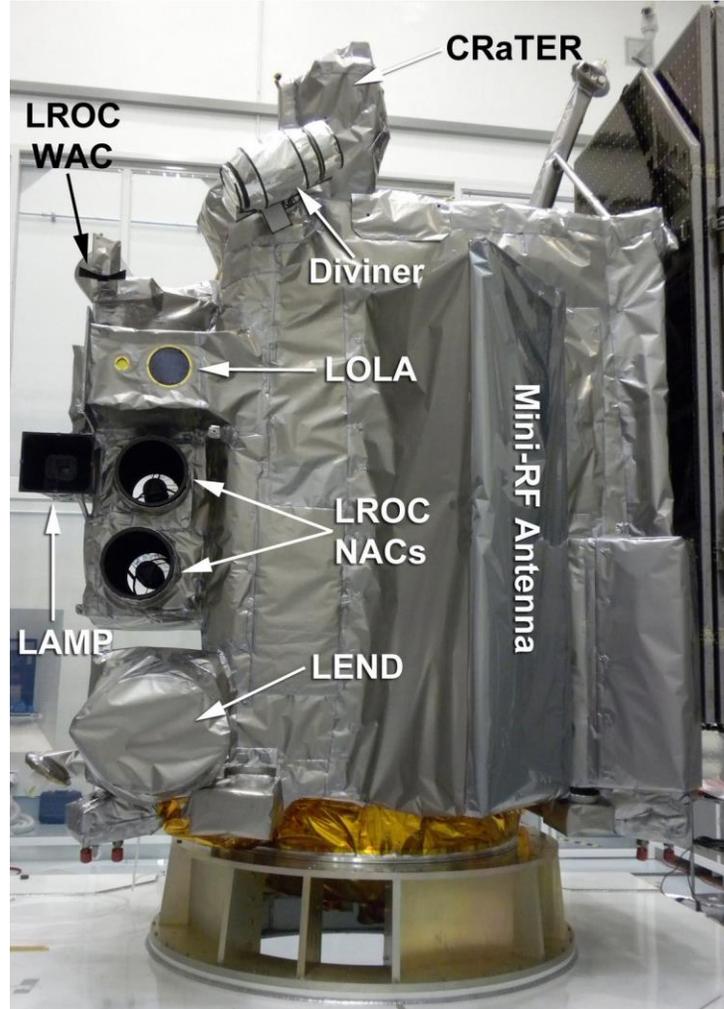
- Target limb not in FoV

Earth

- Dominated by topography and albedo with seasonal variations

- Atmospheric effects: light scattering, clouds
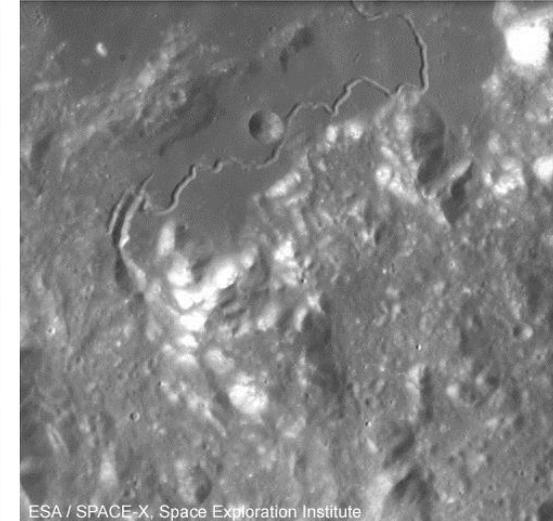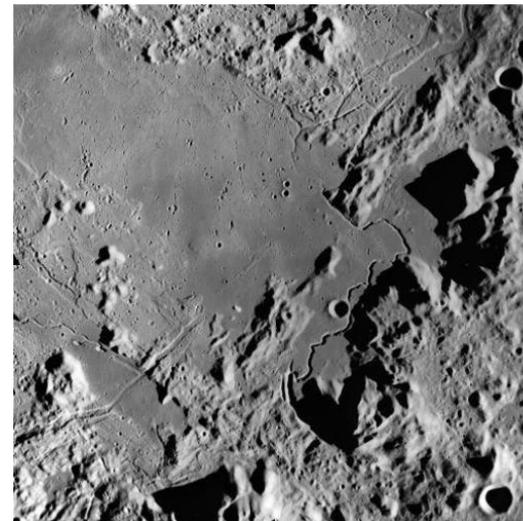
- Target limb not in FoV

Lunar Missions

- Apollo 15

- LRO

- SMART-1

CRaTER

LROC WAC

Diviner

LOLA

LROC NACs

Mini-RF Antenna

LAMP

LEND

ESA / SPACE-X, Space Exploration Institute

Synthetic Image Generation

- Topography data from Laser Altimeter (LOLA) onboard NASA's LRO derived global DTMs

- Using data from Wide Angle Camera (WAC), normalized albedo can be added to the surface model.

- Combining both, an accurate digital twin can be created for rendering synthetic images.

- Global model at 118 metres per pixel

- High resolution South Pole model at 5 metres per pixel
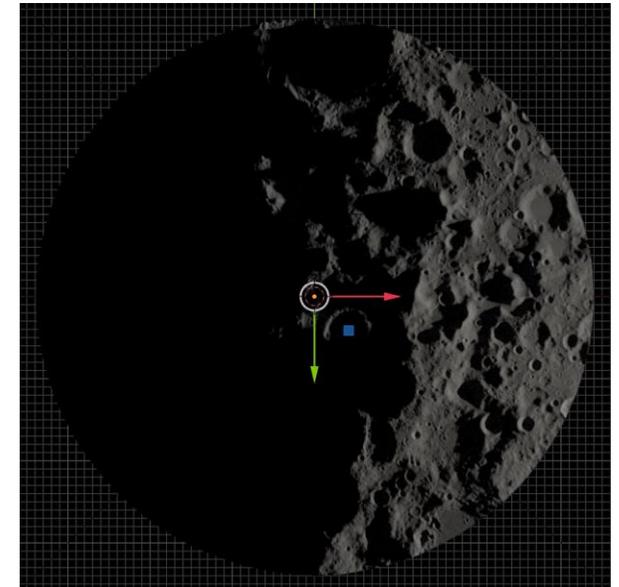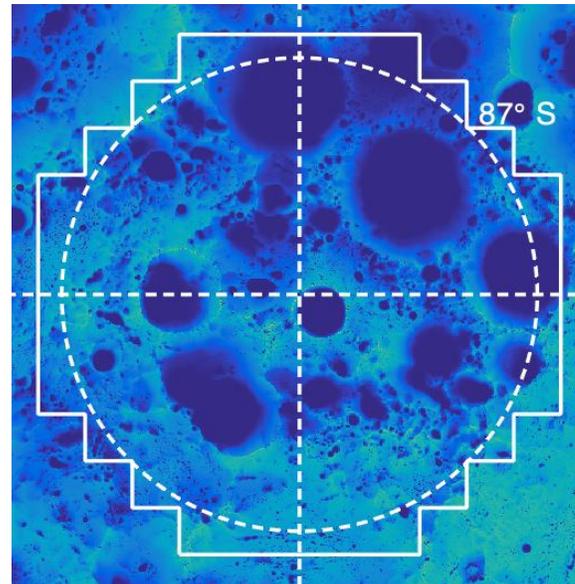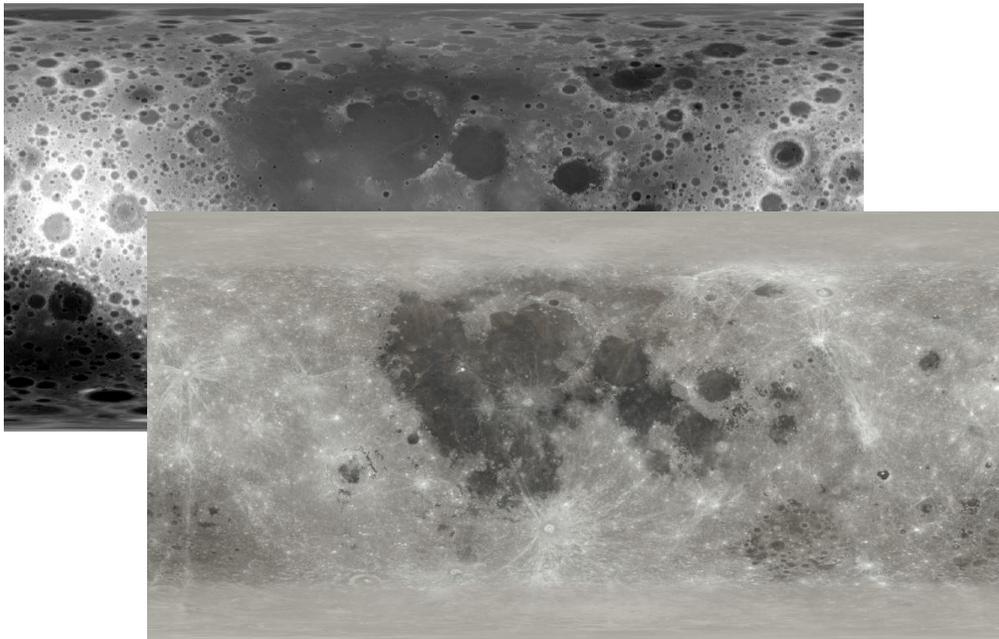
Test Case: Apollo 15

- Orbit and pointing of Apollo 15 Service Module.

- Reproduce illumination conditions from Moon ephemeris and rotation model.

- Mapping Camera instrument model:

  - Aperture and focal distance

  - Image resolution
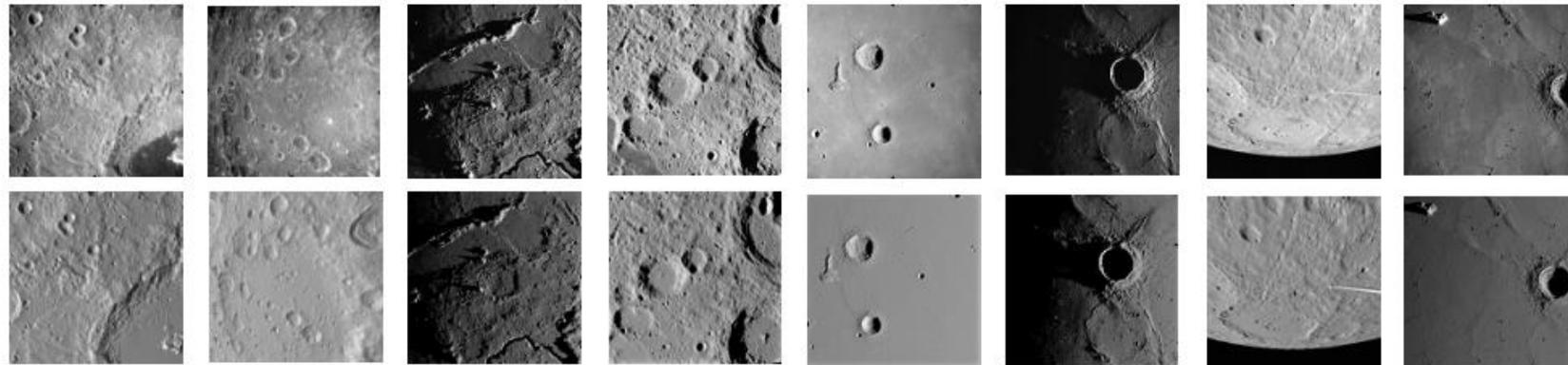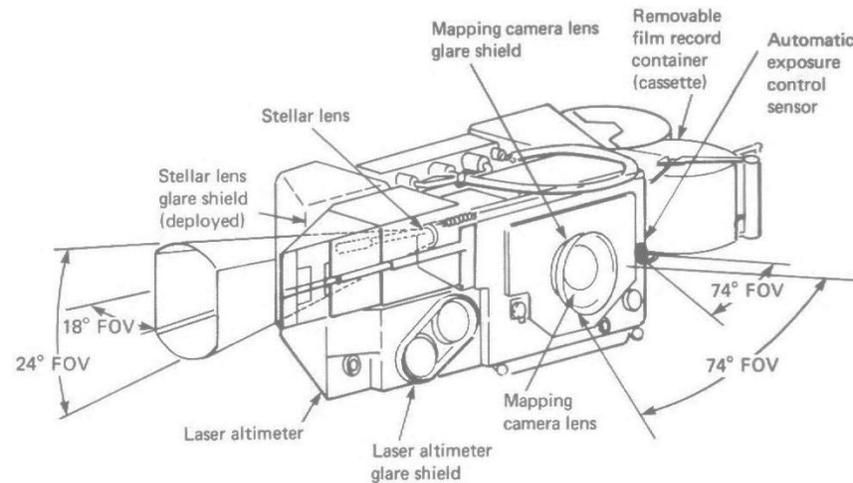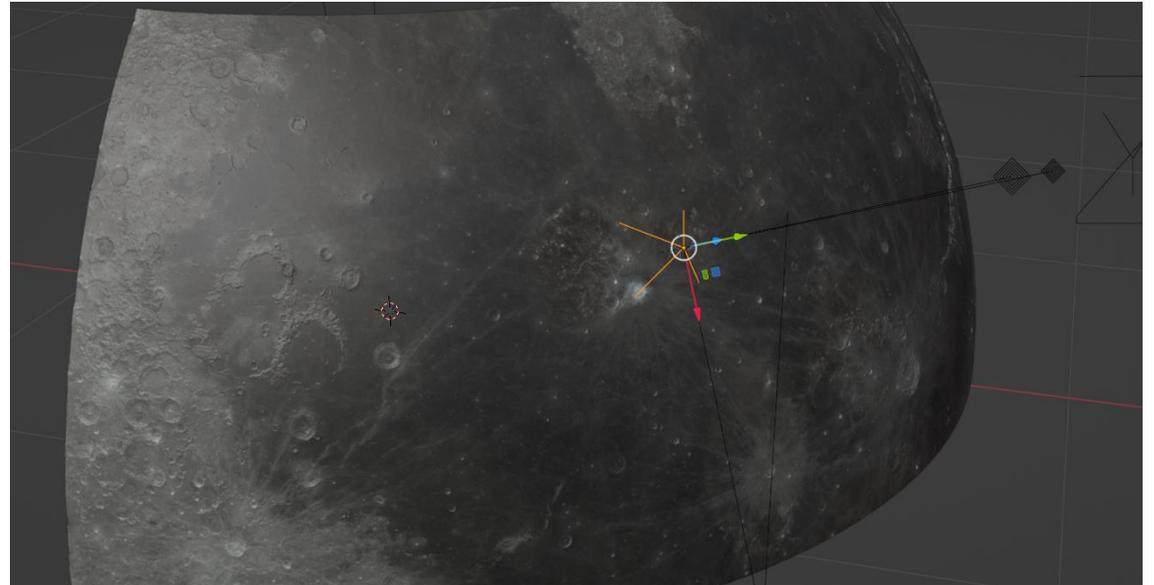
Data Augmentation

- In order to generalize the neural network solution, it has to be trained with multiple geometric and optical effects.

- This effects are introduced in the training set when rendering the images by applying random perturbations of:

  - Altitude and scale

  - Point-of-view and off-nadir

  - Illumination conditions: direction and intensity

  - Gaussian noise

  - Small scale surface variations

- Other effects are applied during training, extending the training set at runtime:

  - Shear and Zoom

  - Pixel intensity histogram shift

  - Random cut-out erase
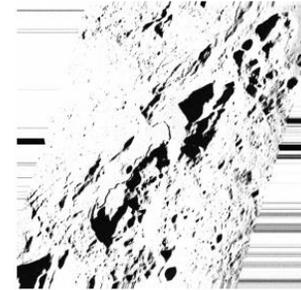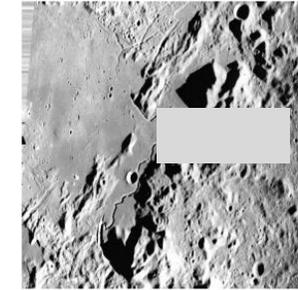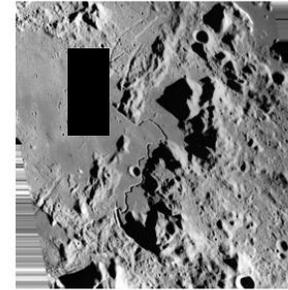
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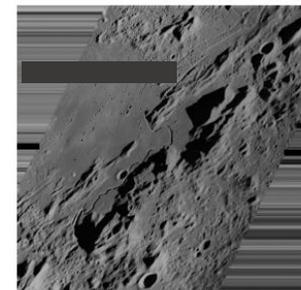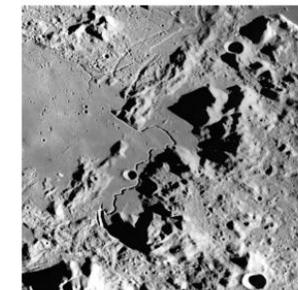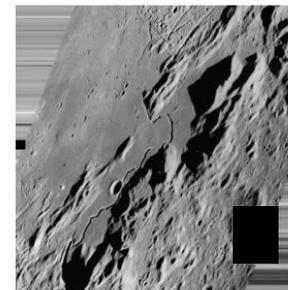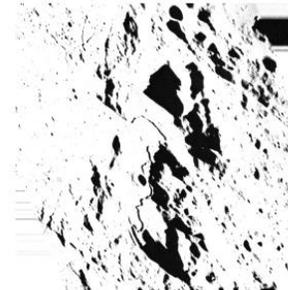
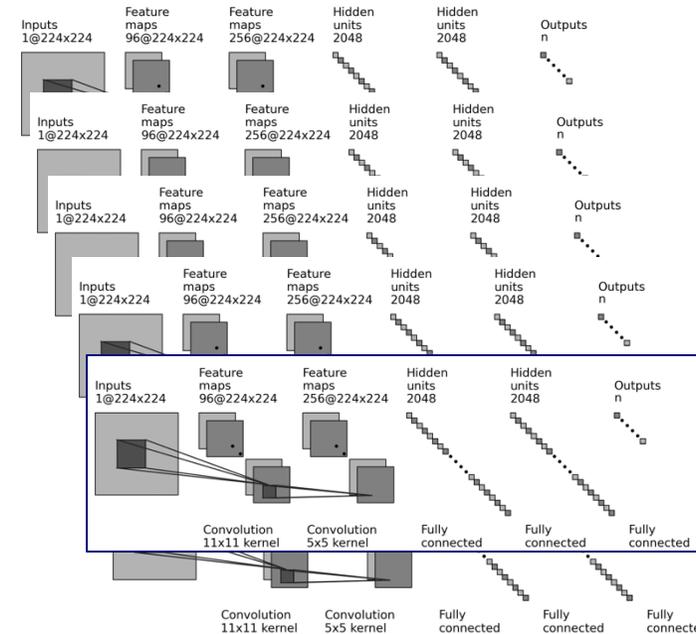# Neural Network Architecture

- **Two levels hybrid CNN**
  - High-Level multiclass classification
  - Low-Level regression for estimating position and attitude
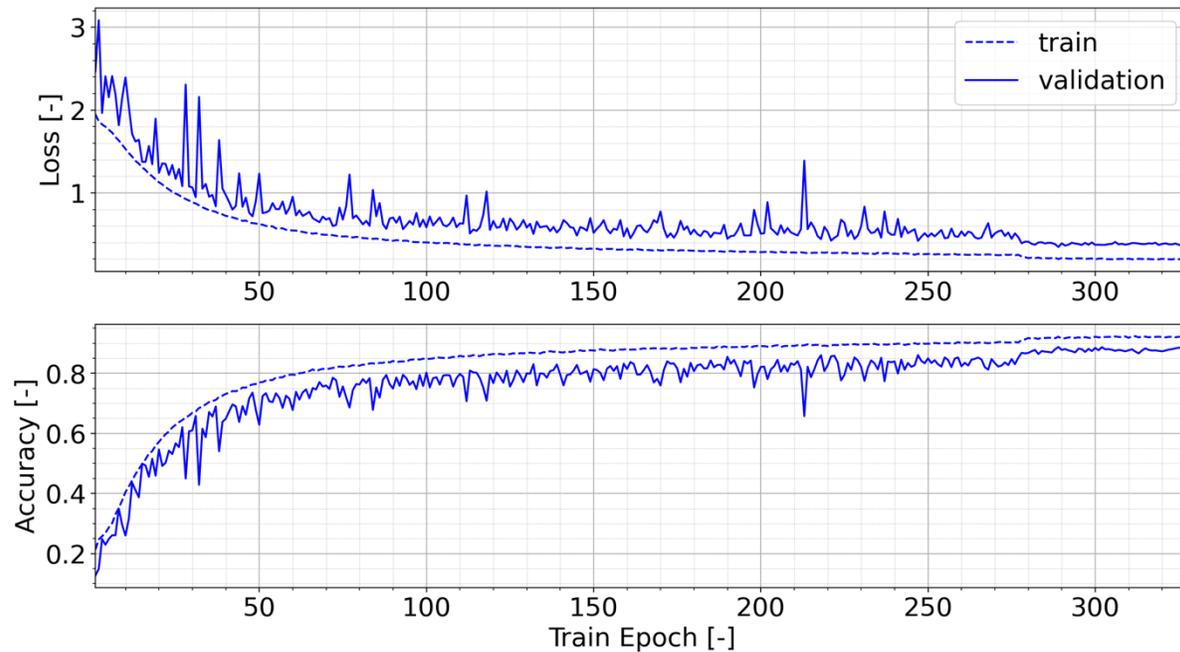   - Set of LL regression CNNs each trained on a single sector of the 3D space

- (X, Y, Z)
- (α, β, γ)
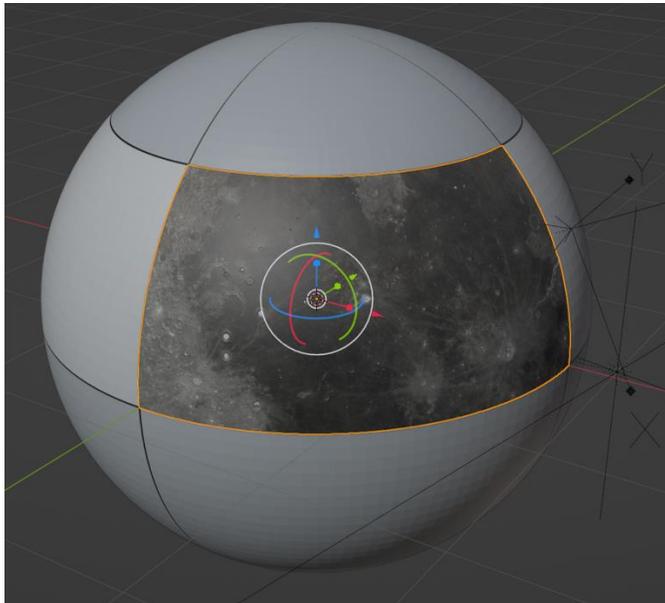
CNN Training and Results

- 16 sectors (4 latitudinal divisions by 4 longitudinal divisions)

- Classification:
  - MobileNetV2 -> 99.47% accuracy

- Regression:
  - VGG19mod
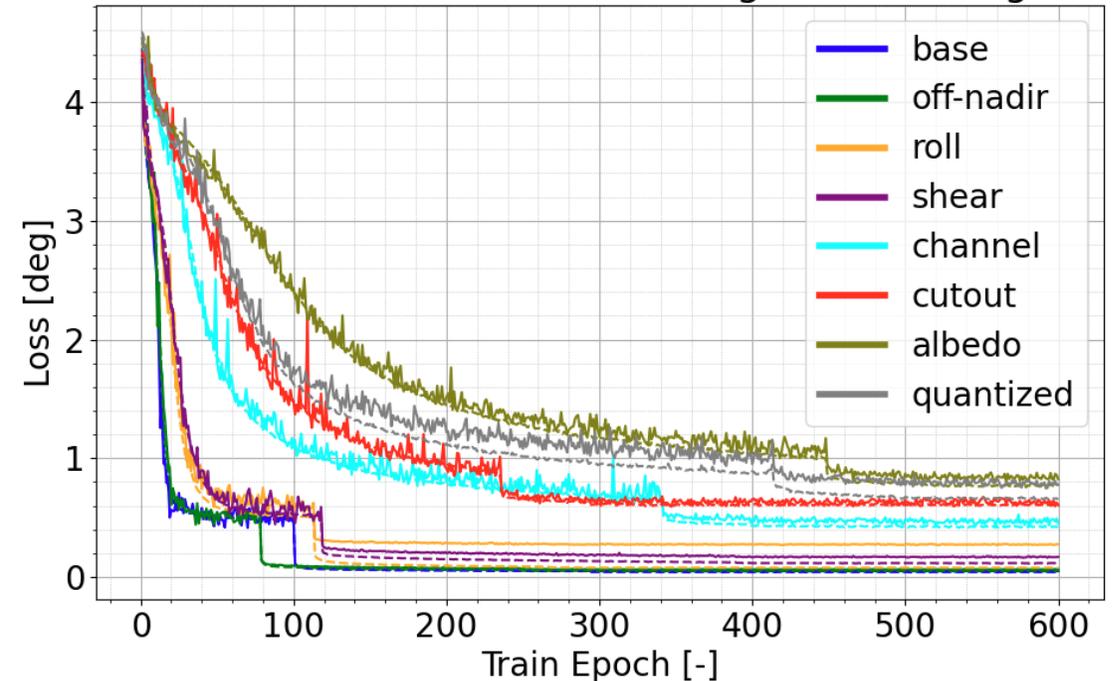
Validation with Real Images

- Using as input real images from the Apollo 15 mapping camera never seen before by the CNN, the accuracy level is maintained when providing real images.

- The CNN model has been tested in an ARM64 Dual Core with 8GB RAM achieving a data rate of 12 frames per second and 62% CPU usage.

- The total size of the model is just 200MB.

Lon: -6.10 Lat: 25.89
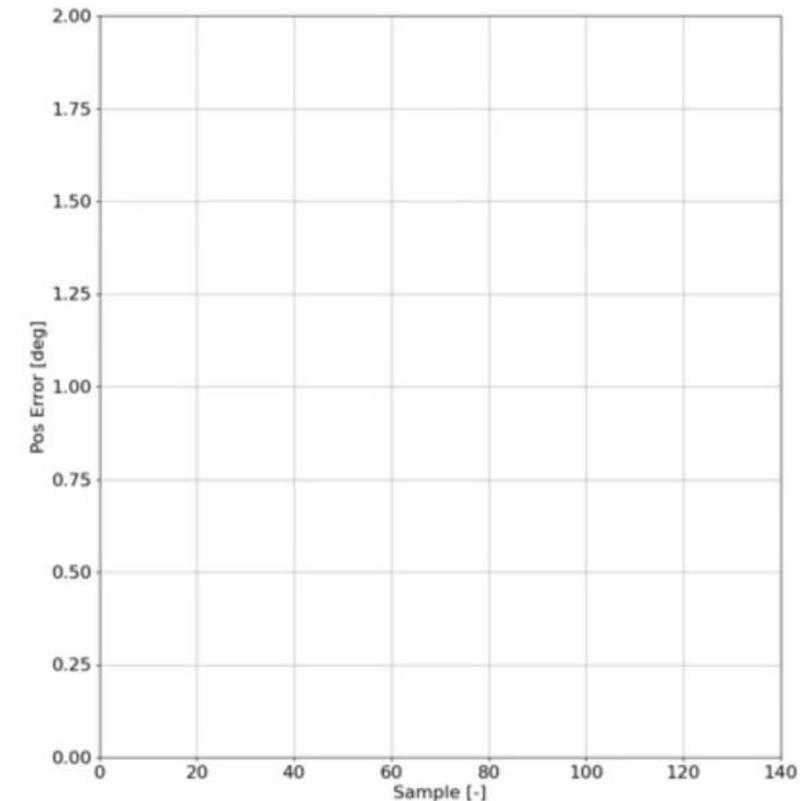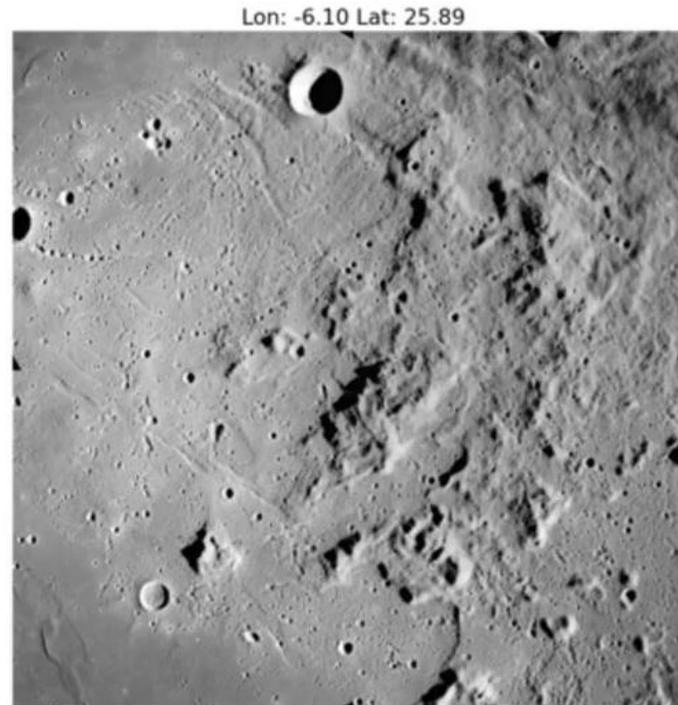
Conclusions

- The trained CNNs have been validated with real images from mission Apollo 15. The CNNs were trained with data from completely different missions.

- The proposed method is applicable to multiple types of celestial bodies:

  - Comets, asteroids, moons, planets

- The implemented lightweight architecture allows the training on-ground to be afterwards uploaded to the spacecraft to be executed on-board during operations.
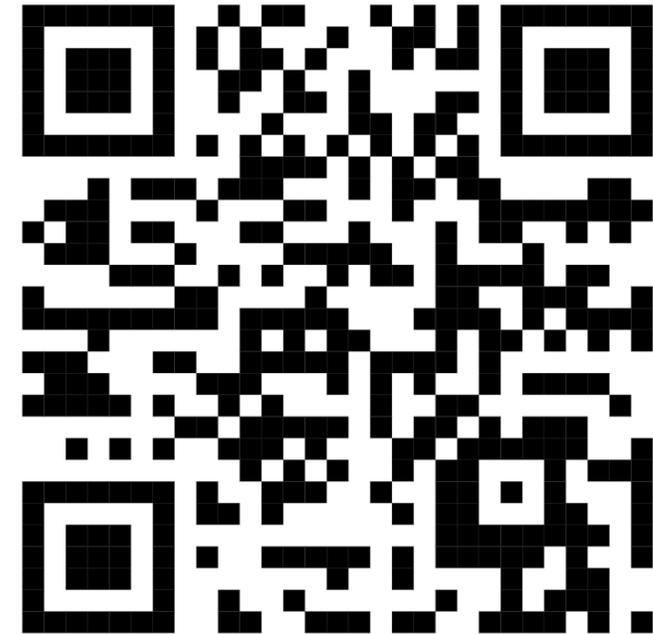
Achievements

- **IEEE Transactions in Aerospace and Electronics** Journal paper published (8th December 2022)

  - Paper published about the development of SPyRender and Churinet, the results of training CNN with space-born instruments synthetic images, and conclusions of applying deep learning for optical navigation in the vicinity of a comet.

- **IEEE Transactions in Geoscience and Remote Sensing** Journal paper published (7th March 2024)

  - Paper published about the development of SPyRender for generating large sets of synthetic images for Planetary Missions and the training and validation of CNNs for Pose Estimation with the OPS-SAT mission.

- **IEEE Transactions in Aerospace and Electronics** Journal paper published (24th January 2025)

  - Paper published about the improvements done on the hybrid-cnn solution architecture, implementing Time Distributed CNNs and integrating the CNN model with a navigation filter.

  - Also extending the images generation process to fill the gap between synthetic and real images.

Thank you for your attention!

Questions?

EarthNet IEEE TGRS paper

BennuNet IEEE TAES paper