

ISRO CHANDRAYAAN MOON MAPPING CHALLENGE

**Team 13
Secondary Team 26**

OVERVIEW

- Introduction
- Dataset Sourcing
- Image Stitching
- Initial Models
- OGSRN: The Final Model
- Results
- Future Expansion Opportunities

PROBLEM STATEMENT

Use Deep Learning models to achieve super resolution for lunar images from TMC-2 instrument onboard Chandrayaan-2. Using these images, create an atlas of the Lunar surface

TARGET

We need an efficient and robust model that

- **Captures fine details of varying terrain**
- **Is adaptive to varied brightness.**
- **Achieves 16x resolution (5m -> 30cm spatial resolution)**

DATASET SOURCING

- A clean and organised dataset was essential to proceed with further research.
- With the vast amounts of data for both TMC-2 and OHRC available on ISRO's website, a pipeline was established.
- We also enlisted the use of NASA's LRO images for variety of data during training

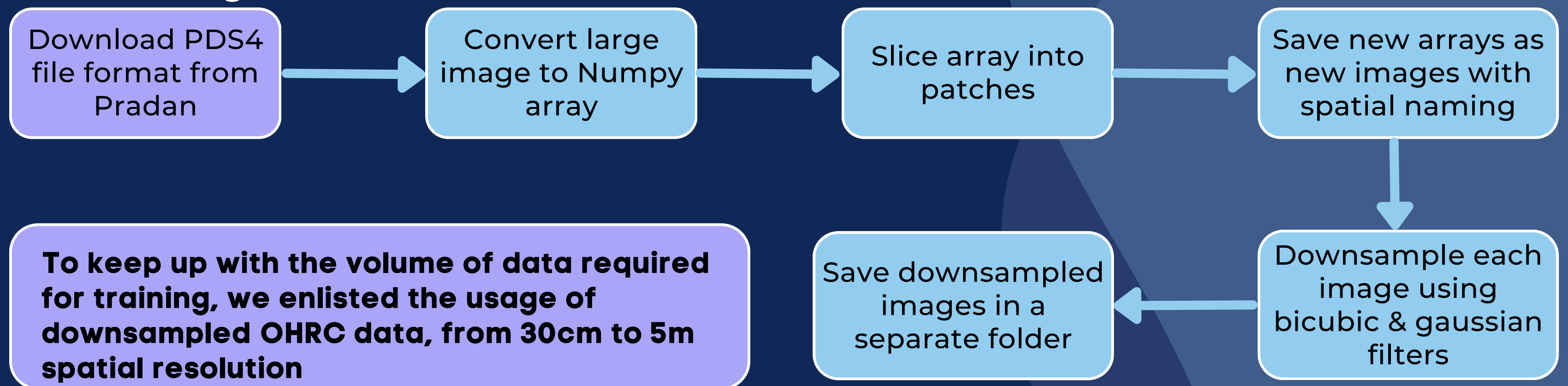
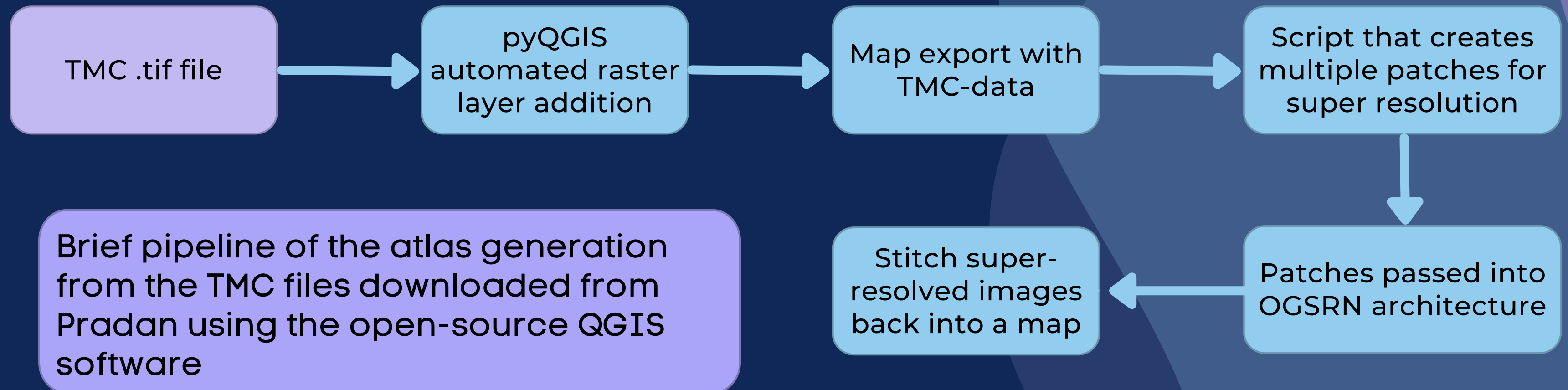
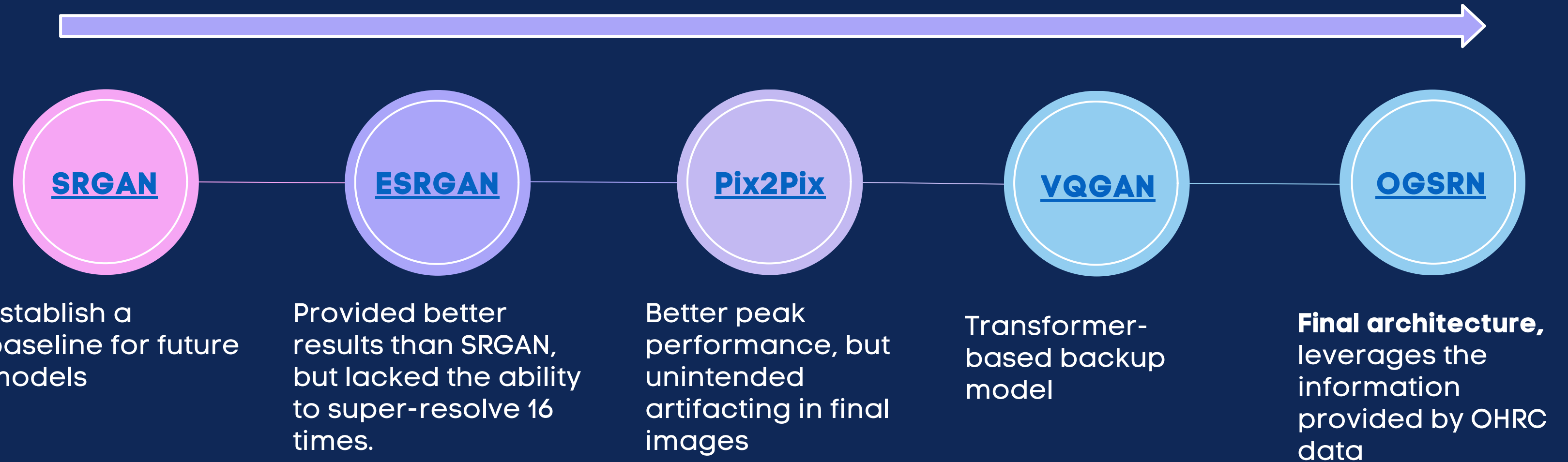


IMAGE STITCHING

- After sourcing the dataset, we parallelly started stitching full-size TMC-images
- However, even after acquiring >1TB of data, all the images were spatially staggered, and not continuous, thus complicating the atlas generation



MODELS THAT WE LOOKED INTO

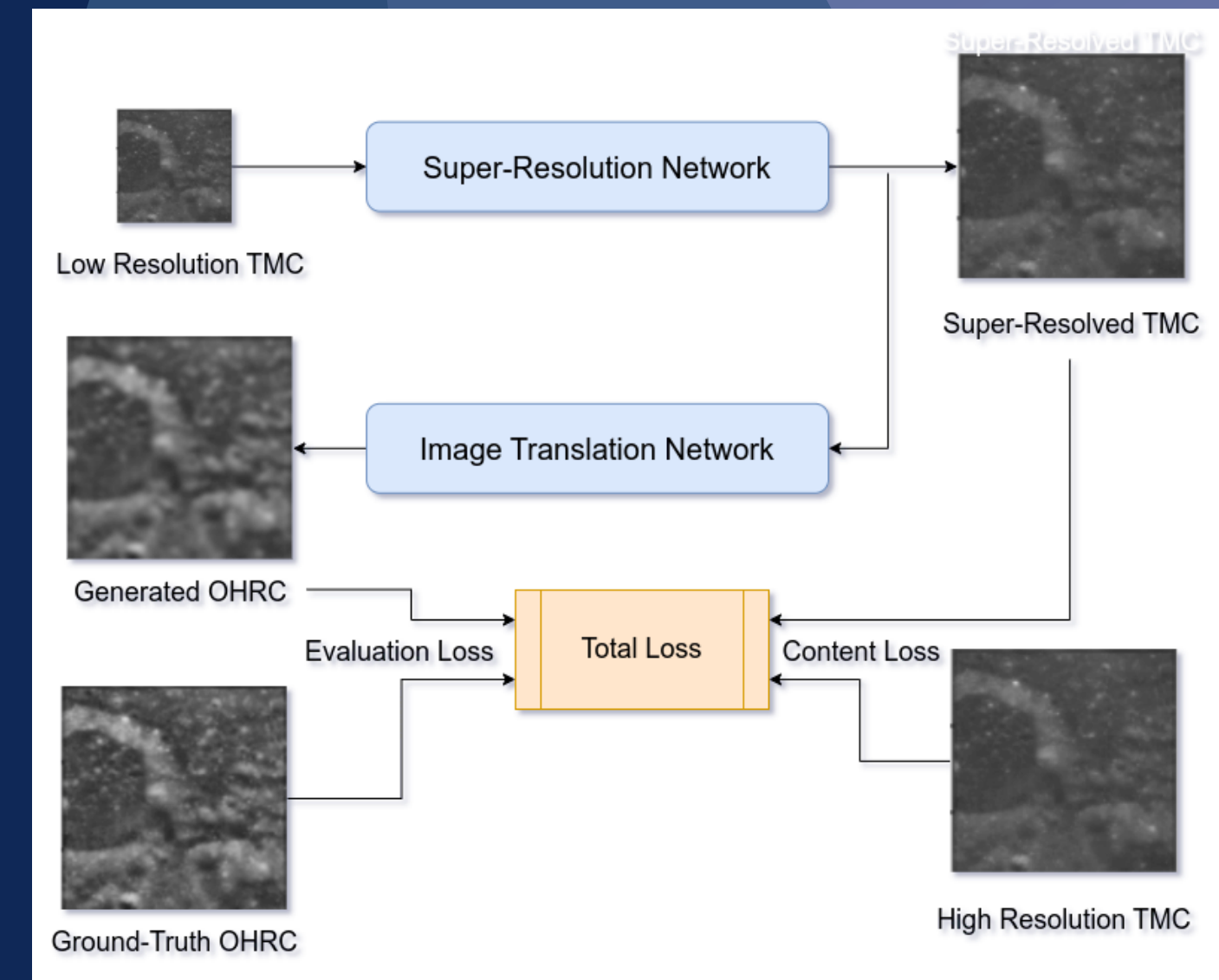


NOTE: Click on the link to access the respective research papers

OGSRN

OPTICAL IMAGE-GUIDED SUPER RESOLUTION NETWORK

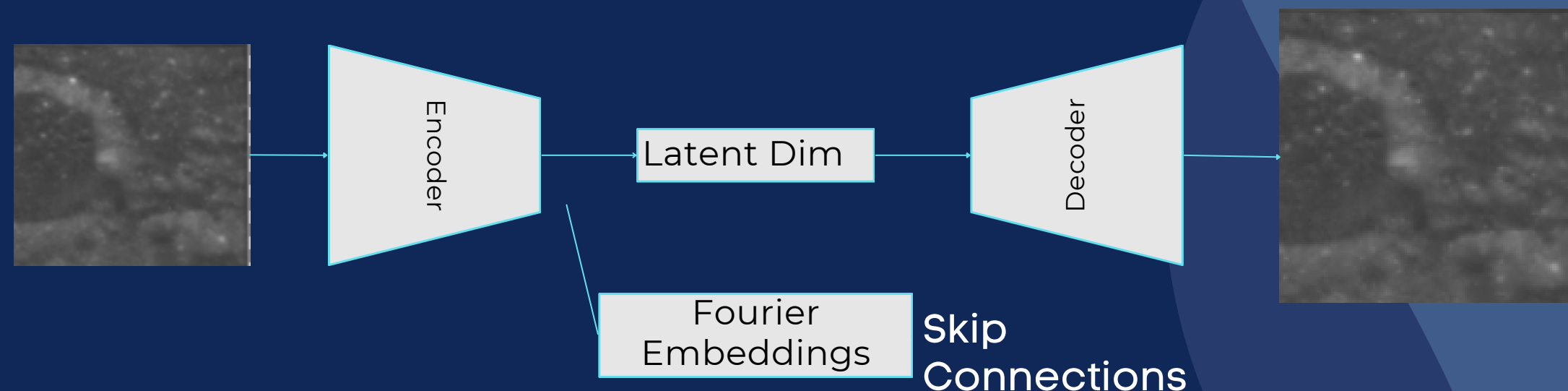
- Standard super-resolution networks leverage Unet-based backbones for super-resolution. TMC images contain coarse features, that are hard to extract using standard deep nets and could lead to over-smoothing of the final output.
- Therefore, we further regularize the training objective by translating the rendered TMC images to OHRC using a pre-trained generator and compare against the RGB ground truth. This guarantees that fine features in the optical images can effectively guide OHRC super-resolution.



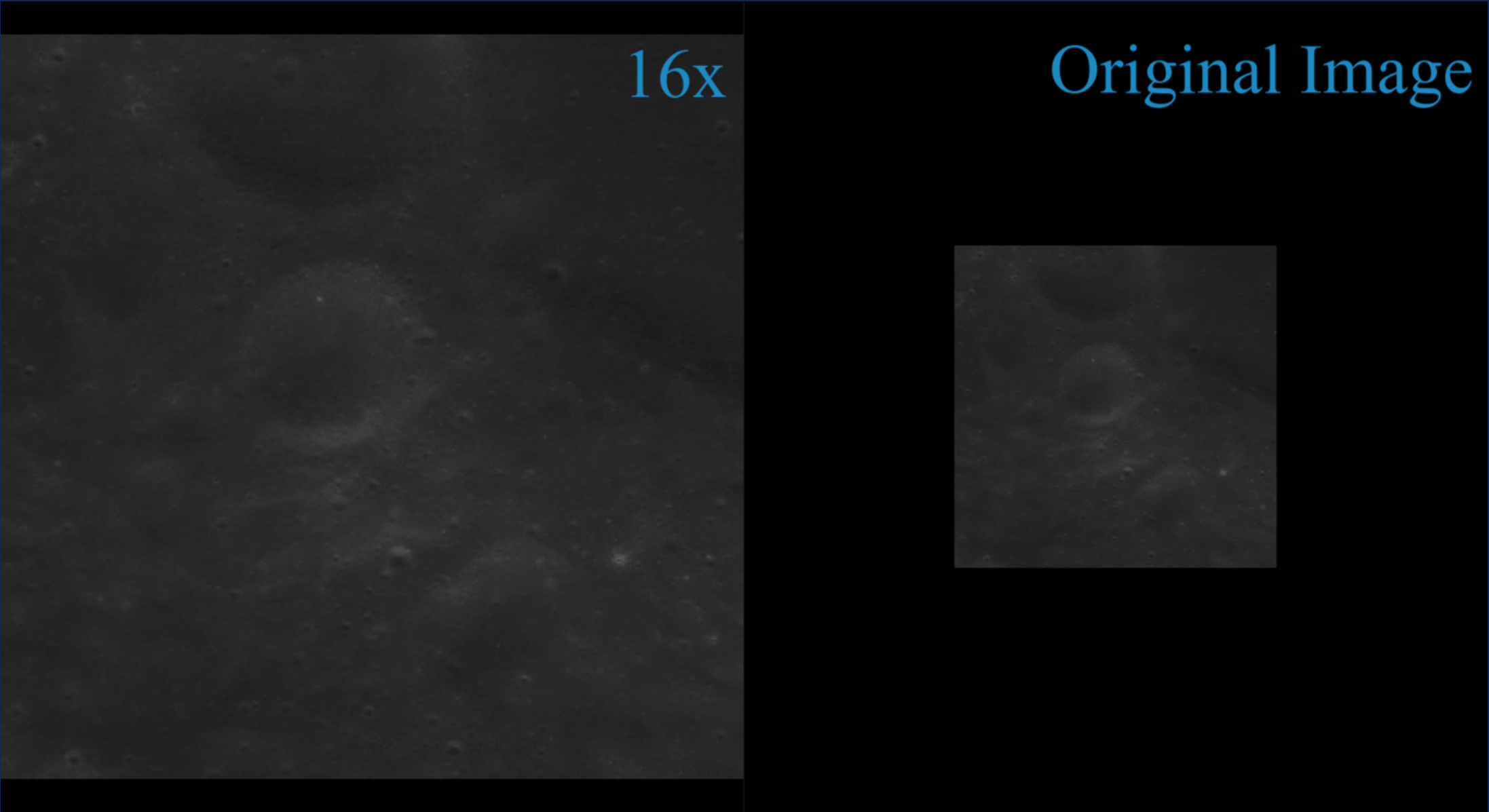
Additional Features of OGSRN

OPTICAL IMAGE-GUIDED SUPER RESOLUTION NETWORK

- Direct 16x super-resolution requires a very large deep network reducing the efficiency.
- Alternate Approach: We perform a two-stage recursive network - each performing 4x upsampling.
- To make the super-resolution input aware, we augment the decoder with fourier embeddings (sin, cos) based on the input resolution. More specifically, the information flow through the skip connections between the encoder and decoder is gated using the fourier embeddings. This allows for super-resolution **from any initial resolution**.



RESULTS



Resolution	PSNR	SSIM
4x	28.26	0.790
16x	22.21	0.702

FUTURE EXPANSION OPPORTUNITIES

Crater detection and SR

- Using [this](#) open-source database, we looked into extracting and super-resolving just the craters and stitching it back.
- We also looked into the possibilities of using object detection to super resolve particular features like boulders

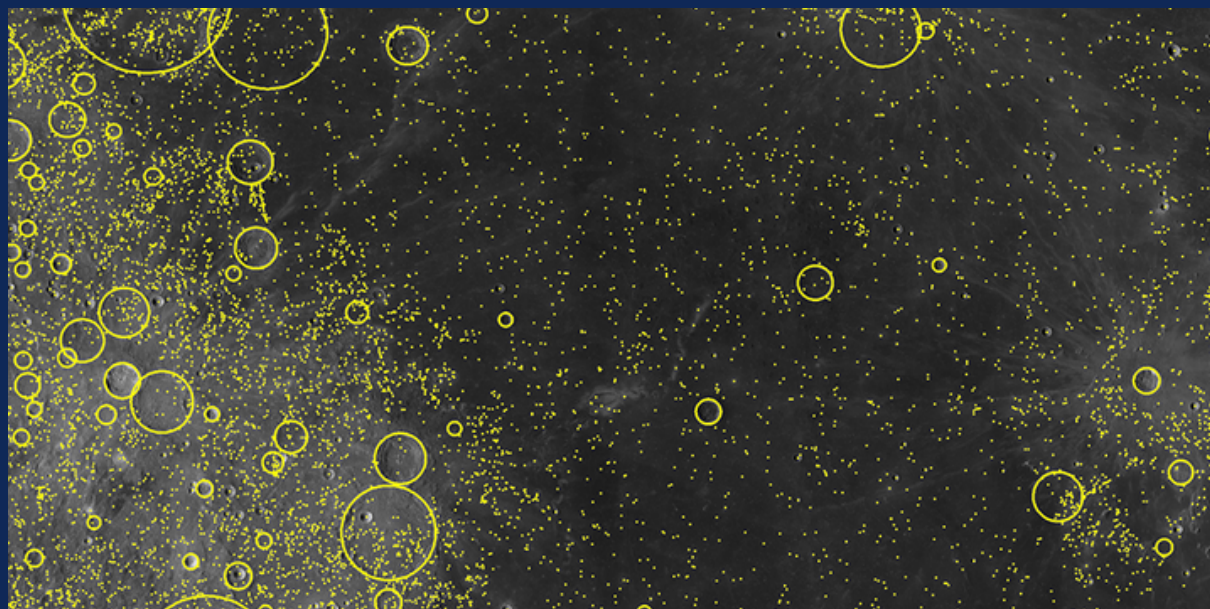


Image of all the craters identified by the database

Training with desert images on Earth

- Training with grayscale desert satellite images at high resolution (>30cm) would enable even higher detail of the lunar surface

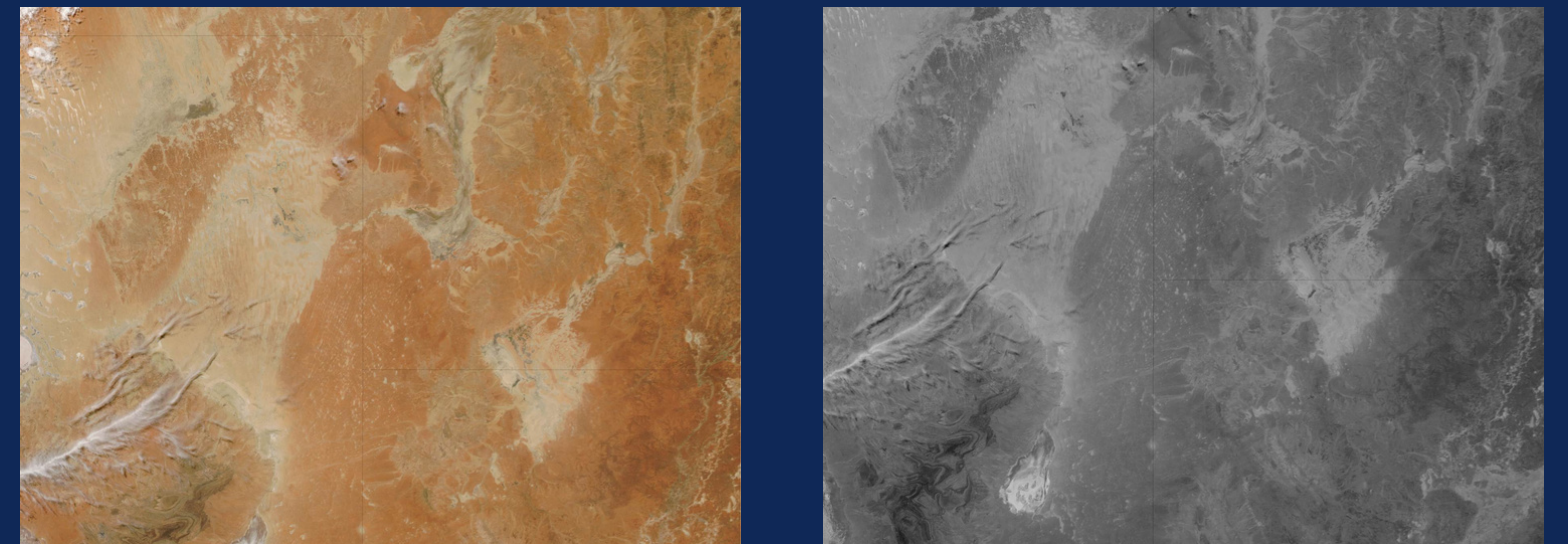


Photo of a desert on earth converted to grayscale



THANK YOU