SUPER RESOLUTION OF JOVIAN ICY SATELLITES USING NEURAL NETWORKS

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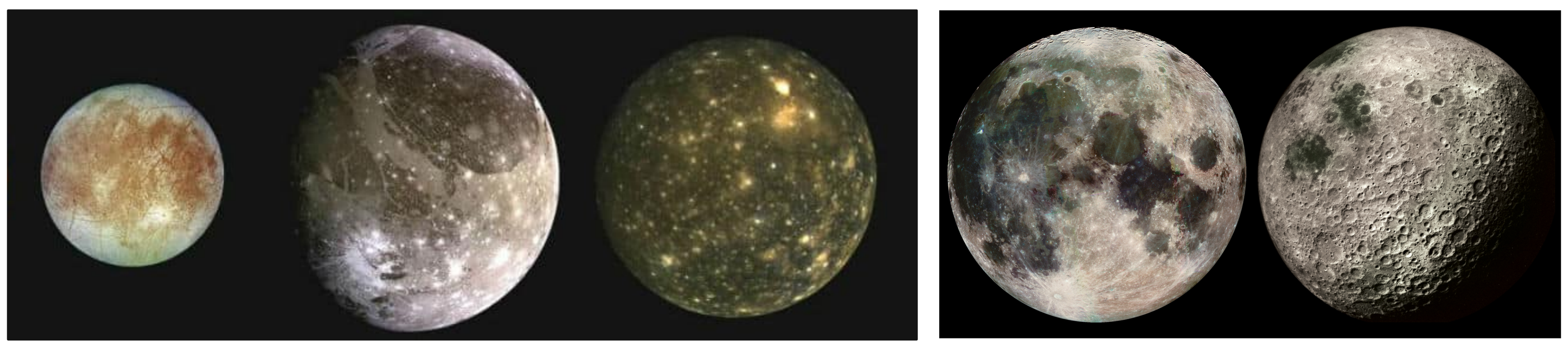
1 - INTRODUCTION

Higher resolutions are highly desirable for planetary science. Super resolution is the process of algorithmically upscaling a lower resolution image (e.g. using bicubic interpolation). Based on popular research datasets for image processing, neural networks outperform previous super resolution techniques.

In this project, we used two neural networks (SRCNN and ESRGAN) for super resolution of planetary surfaces. We use low and high resolution images from the Moon to train and test our approach, as it has surfaces features similar to the Jovian icy satellites (figure 1).



(a) (b)

Figure 1: (a) From left to right, surface images of Europa, Ganymede and Callisto. Image credit: NASA/JPL/DLR. **(b)** From left to right, surface images of the bright and dark side of the Moon. Image credit: (Left) NASA/JPL/Caltech (NASA photo # PIA00405); (right) F.J. Doyle/National Space Science Data Center.

2 - METHOD

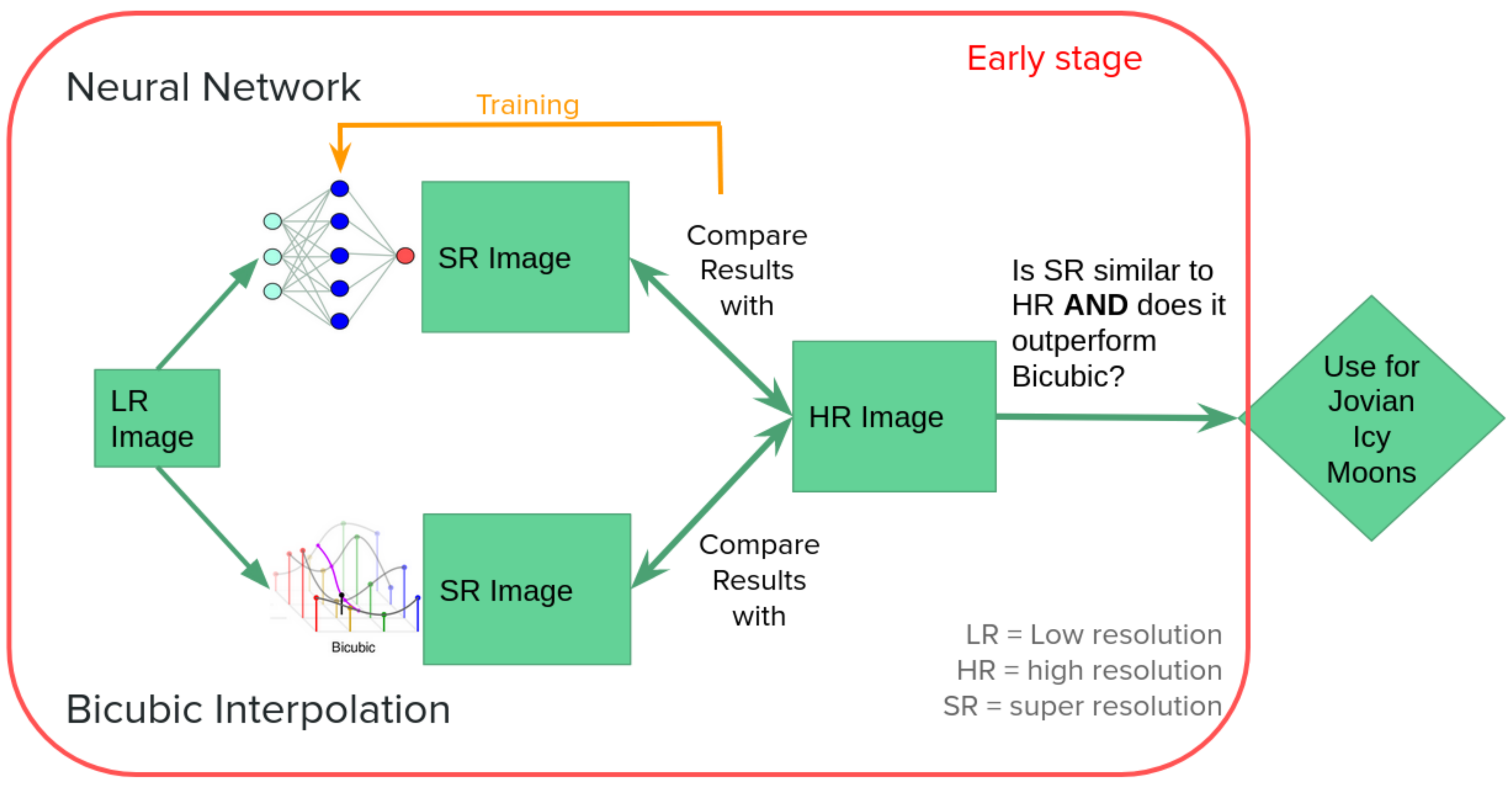


Figure 2. An overview of adapting neural network based super resolution models for the Jovian Icy Moons.

- During training, the LR images of the moon are fed into the neural network to produce a SR image.
- The SR image is compared with the HR image. If it's not similar to the HR image, the network is retrained using adjusted parameters.
- This is repeated until no substantial improvements can be made. The network can now be used for predictions.
- During prediction, LR image is fed into both the neural network and the bicubic interpolation models.
- If the SR image outperforms bicubic and closely matches HR, the trained network can then be used for Jovian Icy moons.
- As we're in an early stage, we're only focusing on the training process.

3 - METRICS

Mean Squared Error

$$MSE(f,g) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(f_{ij} - g_{ij})^2$$

Peak Signal to Noise Ratio

$$PSNR(f,g) = 10\log_{10}\left(\frac{255^2}{MSE(f,g)}\right)$$

Structural Similarity Index

$$SSIM(f,g) = l(f,g)c(f,g)s(f,g)$$

f is the reference image of dimensions M x N
g is the test image
l is the luminance comparison function
c is the contrast comparison
s is the structure comparison function

Brightness is also used as a proxy for the geometric albedo, α, which is the radiation compared to a ideal, fully reflecting surface.

4 - RESULTS

Once the network is trained, the results from SRCNN and ESRGAN were compared to the high resolution image as well as the outputs from bicubic interpolation. The results for 3 sample images are shown in figure 3.

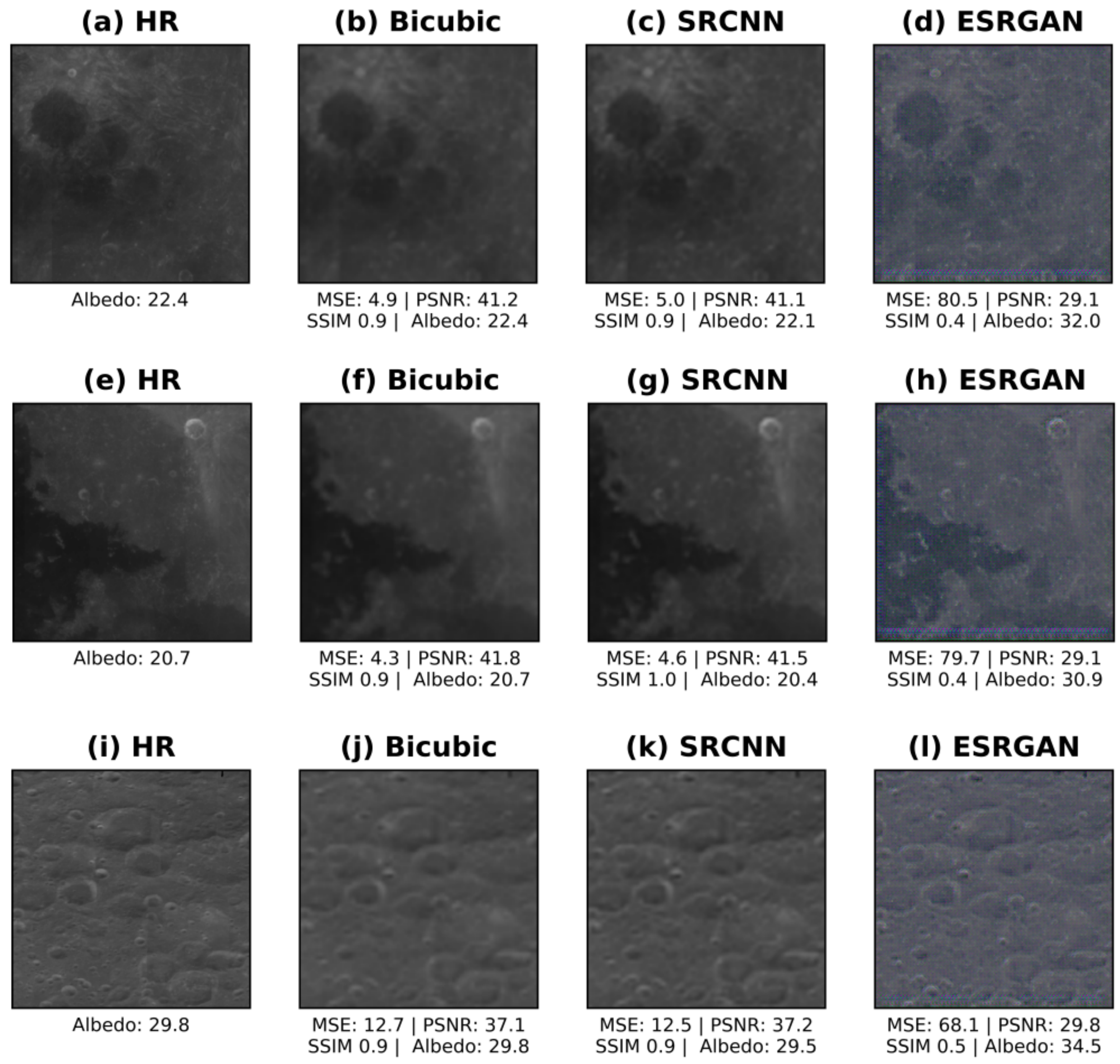


Figure 3. Subplots showing the metric comparison between the high resolution groundtruth image (HR) shown by (a), (e), and (i), with bicubic upsampled images (bicubic) shown by (b), (f) and (j), SRCNN shown by (c), (g) and (k) and ESRGAN shown by (d), (h), and (l). Note that PSNR is in units of decibels, and albedo is in units of percent.

Table 1. A table of mean and standard deviation of metrics based on the testing dataset of 50 images. Note that S.D. stands for the standard deviation. The MSE, PSNR and SSIM values are computed betweent the HR image and the outputs from the 3 other models.

	α		$\Delta\alpha$		MSE		PSNR		SSIM	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
HR	24.291	6.150	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Bicubic	24.293	6.151	0.002	0.003	6.334	3.247	40.691	2.274	0.929	0.028
SRCNN	24.039	6.110	0.252	0.102	6.439	3.091	40.542	2.105	0.933	0.026
ESRGAN	32.305	2.590	8.014	3.614	74.945	8.207	29.412	0.514	0.463	0.070

5 - CONCLUSIONS

SRCNN has achieved a similar performance to bicubic interpolation, though its mean is consistently below that of bicubic interpolation. A deeper architecture might be needed to improve its performance.

For ESRGAN, all metric values show that the network performs less well than bicuic interpolation and SRCNN. Its albedo values are much higher than the original high resolution input, which could be the cause of underperformance. The cause of the high albedo may be attributed to undertraining.

6 - FUTURE DEVELOPMENT

To further develop this project, one needs to train both SRCNN and ESRGAN for more iterations. As SRCNN has a very simple architecture, it may be beneficial to increase its complexity by adding the more layers from a range of varieties. This will require more powerful computational resources.

If neither works, it may be beneficial to explore alternative models that are more catered to remote sensing, such as enhanced deep residual networks, by [3].

REFERENCES

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