*International Journal of Engineering Science Invention (IJESI)*
*ISSN (Online): 2319-6734, ISSN (Print): 2319-6726*
*www.ijesi.org ||Volume 11 Issue 6 Series II || June 2022 || PP 01-06*

# Super-Resolution of Mars Satellite Images Using Convolutional Neural Networks

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***ABSTRACT:*** *Super-Resolution (SR) is one of the base problems of the computer vision domain. Upscaling of a low resolution (LR) image to its high resolution (HR) version is a vague problem with a vast solution space since multiple mappings exist between LR and HR images. Deep Learning networks have been utilized to provide an efficient and robust solution to the SISR problem. A vast amount of research has been made in the domain, but most present work focuses on more general applications of SISR. However one of the most useful applications that super-resolution can provide is in the domain of remote-sensing and the study of satellite imagery. There exists a gap in the research into the application of SISR to maximize the information gained from satellite image analysis, especially with respect to Mars since these images pose additional difficulties due to their nature. In our work, we study the application of a deep learning based SR model, named Super-Resolution Convolutional Neural Networks on a custom-built dataset of near-infrared satellite images of Mars. A comprehensive overview of the model as well as of its performance for the given task are provided in this work.*

***KEYWORDS -*** *Image Processing, Deep Learning, Neural networks, Remote Sensing, Super-Resolution*

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Date of Submission: 13-06-2022 Date of Acceptance: 27-06-2022

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## I. INTRODUCTION

Super-resolution (SR) is defined as the task of upscaling a low-resolution to a high-resolution version while maintaining as much detail from the original image as possible.The image reconstruction offers a methodology for correcting imaging system imperfections. The low-resolution image can be represented as[1]:

$$□□ = □_{□}[(□ \otimes □)] + □□□□□ \quad (1)$$

where □ ⊗ □ is the convolution between the blurry kernel □ and the ground truth image □, $□_{□}$ is the downsampling operator with scale factor □, and □□□□□ is the independent noise term. The goal of SISR is to reverse this process, which proves to be a challenge since multiple different solutions exist to this problem.

As with many other computer vision problems, SR can be approached through the lens of deep learning convolutional neural networks(CNNs), which have now outperformed traditional SR algorithms that relied on mathematical processes that tried to smoothly interpolate the known pixels of an LR image to those of an HR image [2]. These mathematical methods are the equivalent of a convolution with a kernel independent of the image. These methods, lack in performance and produce overly smooth images with a loss of detail, to counteract this we utilize CNNs that learn kernel states with non-linear activation functions to encode high dimensional features into simplified filters that represent general characteristics about the images that can add structure lost in the low-resolution input.

Additionally, the super-resolution of satellite images poses more problems that need to be addressed. Since CNNs were introduced to tackle 8-bit RGB images [3], satellite image products that are generally calibrated to represent a physical unit, such as surface reflectance or absolute radiance have to undergo various pre-processing steps such as depth reduction, colorspace conversion, etc. in order to make them suitable to feed into the model. Satellite images are also prone to high degrees of variance due to physical conditions such as haze, clouds, and cloud shadows as well as land cover characteristics that vary globally to a high degree.

## II. SUPER-RESOLUTION CONVOLUTIONAL NEURAL NETWORKS (SRCNN)

2.1. Background

In what is considered the seminal work on the subject of Deep learning for Super Resolution, Dong et al.[4] described how traditional sparse representation techniques can also be thought of as a deep convolutional network. A convolutional network aims to reduce a high dimensional image to its most essential features to reduce the computational required to process them. So they introduced SRCNN, which is a pre-upsampling SR network that aims to show how the steps of a sparse-coding based method, namely:

- Patch or feature extraction is the process of representation of raw image data as numerical features that can be easily processed while preserving the information from the original image,
- The non-linear mapping layer aims to alter the number of channels and map the features of the low-resolution image to those of the high resolution image .
- Reconstruction that is responsible for reconstructing the super-resolved image at the output could be represented as a network of convolutional layers.

2.2. Architecture

SRCNN has a fairly simple structure as shown in the figure below, consisting of convolutional, and ReLU(Rectified Linear Unit) activation layers.[4] It is trained to work based only on the luminosity, i.e the intensity of the pixels that make up the image.

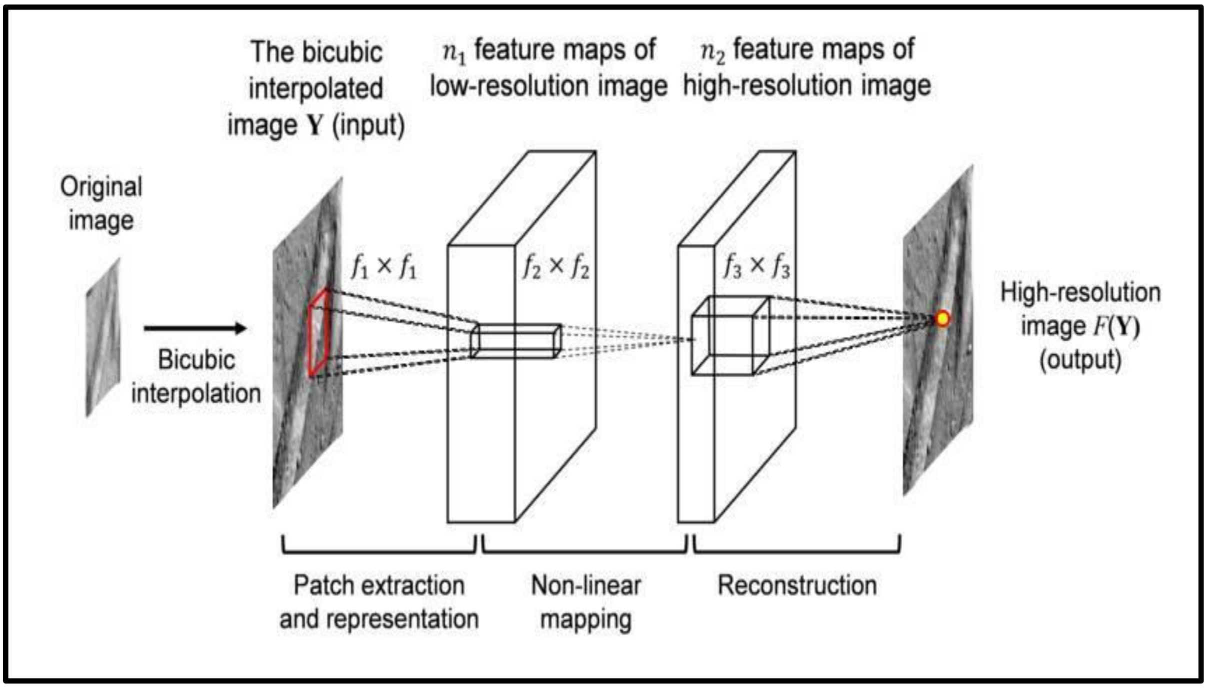


**Fig.1**. SRCNN Block Diagram

The SRCNN model can be split into 4 sections:

2.2.1. Bicubic Interpolation

Since SRCNN is a pre-upsampling network, its aim is to help increase the SR accuracy of a pre-interpolated image rather than generate an HR image directly from the LR image. For this we make use of the bicubic interpolation technique as represented in equation (5), where X is the LR image, and Y is the bicubically interpolated intermediate image that is then fed in as the input of the SRCNN net:

□ = □$_{□□□□□□□}$(□) (5)

2.2.2. Patch Extraction and Representation

The first layer performs a standard convolution with ReLU to get □$_1$(□) [4] that is a set of feature maps of the image:

□$_1$(□) = □□□(0, □$_1$ ∗ □ + □$_1$) (6)

where □$_1$ is the weight kernel, whose size is given as □□□□ □□ □$_1$ = □ × □$_1$ × □$_1$ × □$_1$, and □$_1$ is the bias vector whose size is □$_1$ = □$_1$. Here □ is the number of channels to be considered, □$_1$ is thesize of the kernel, and □$_1$ is the number of filters in the first layer. In our model, □ = 1, □$_1$ = 9, □$_1$ = 64.

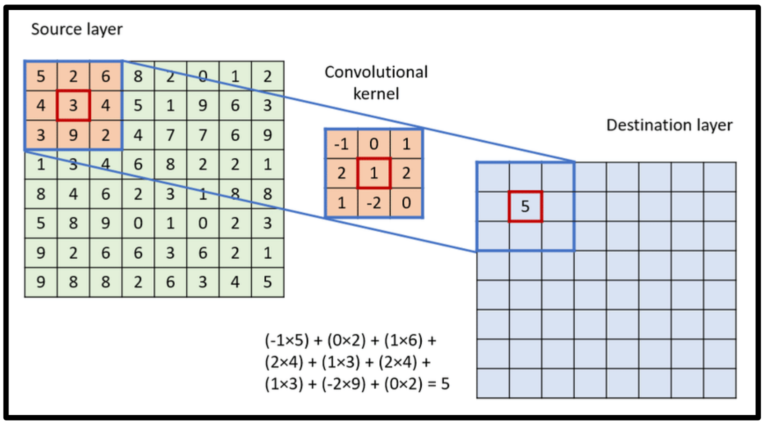


Fig.2. Convolution Process

2.2.3. Non-Linear Mapping

The second layer performs a non-linear mapping with the aim of mapping the features extracted from the interpolated image to the high-resolution output[4]:

$$\square_2(\square) = \square\square\square(0, \square_2 * \square_1(\square) + \square_2)\ (7)$$

where the $\square\square\square\square$ $\square\square$ $\square_2 = \square_1 \times \square_2 \times \square_2 \times \square_2$, and the size of $\square_2 = \square_1$. Here $\square_1$ is the convolutional kernel size of the first layer, $\square_1$ & $\square_2$ are the number of features extracted in layers 1 and 2. In our model, $\square_2 = 1, \square_1 = 64$ & $\square_2 = 32$. This 1×1 actually is a convolution suggested in Network In Network (NIN) [5]

2.2.4. Reconstruction

The final layer is responsible for reconstructing the image, by performing another calculation as [4]

$$\square_3(\square) = \square_3 * \square_2(\square) + \square_3\ (8)$$

where the $\square\square\square\square$ $\square\square$ $\square_2 = \square_2 \times \square_3 \times \square_3 \times \square$, and the size of $\square_2 = \square$. Here $\square_2$ is the filter size of the third convolution layer and $\square_2$ is the number of filters in layer 2. In our model, $\square_3 = 5, \square = 1, \square_2 = 32$.

2.3. Loss Function

We calculated MSE over each of the 3 image channels to compare the pixel for pixel difference between the ground truth image and the output of the SRCNN network. [4] It is calculated using eq.(2) where the mean of the pixel errors is squared. Our model utilizes MSE as its loss function to guide its training.

## III. EXPERIMENTAL RESULTS

3.1. Datasets

Since no standard dataset of Mars satellite images exist for super-resolution, we improvised and created a training set of 1000 images. For this, we utilized the DoMars16k dataset[5] which is a diverse classification dataset of landforms on Mars. It contains 16150 hand-labeled images derived from the raw near-infrared images captured by the HiRISE camera on NASA's Mars Reconnaissance Orbiter. The dataset consists of images with dimensions of 200px * 200px, representing 15 unique classes of landforms on Mars. This gave us a diverse enough set of images to provide our algorithm with enough varied data to perform well on most images. We chose 1000 images at random from the dataset and split it into 800 training, 100 test, and 100 validation images.

3.2. Implementation Details

As stated already our model is built with internal parameters: number of input channels (c): 3, number of layer 1 feature maps ($\square_1$): 64, number of layer 2 feature maps ($\square_2$): 32, kernel size of 1st convolutional layer ($\square_1$): 9, kernel size of 2nd convolutional layer ($\square_2$): 1, kernel size of 3rd convolutional layer ($\square_3$): 5.

While training we set out hyperparameters with the following values: our scale factor was 2x, the learning rate was 0.0001, the batch size was 300, we ran the training over a total of 20 epochs, and utilized 8 workers in the data loader, our random number seed was set to 123.

3.3. Measured Test Metrics

We quantitatively measured the performance of our SR algorithm, to measure how well the image was reconstructed by the model. For this, we decided to use 2 metrics:

3.3.1. Peak Signal-to-Noise Ratio (PSNR)

PSNR of an image is a logarithmic measure of the ratio between the maximum possible value that a signal can have to the mean of the squared error measured across each pixel in the image. PSNR is computed using the following equations:

$$MSE = \frac{\sum_{M,N}[I_1(m,n)-(I_2(m,n)]^2}{M*N} \ (2), \quad PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right) \ (3)$$

where $M$ and $N$ are the width and height of the image in pixels and $R$ is the maximum value a pixel of the image can have.

3.3.2 Structural Similarity Index Measure (SSIM)

SSIM is a measure of the perceptual similarity of structures between the ground truth image and the test image. SSIM values range from -1 to +1, where +1 indicates perfect structural similarity

3.4. Results

Training of the SRCNN model was conducted on google collab, where it took us 2 hours and 18 minutes on a Google Compute Engine GPU over 20 Epochs.

TABLE 1. Achieved Training Metrics over 20 epochs

| **Lowest MSE Loss** | **Highest PSNR (dB)** | **Highest SSIM** |
|---|---|---|
| 0.0004753 | 34.837 | 0.861 |

TABLE 2. Averaged test results over 100 image dataset

| **SR-Algorithm** | **Average PSNR (dB)** | **Average SSIM** |
|---|---|---|
| *Bicubic* | 34.084 | 0.810 |
| *SRCNN* | 35.508 | 0.867 |

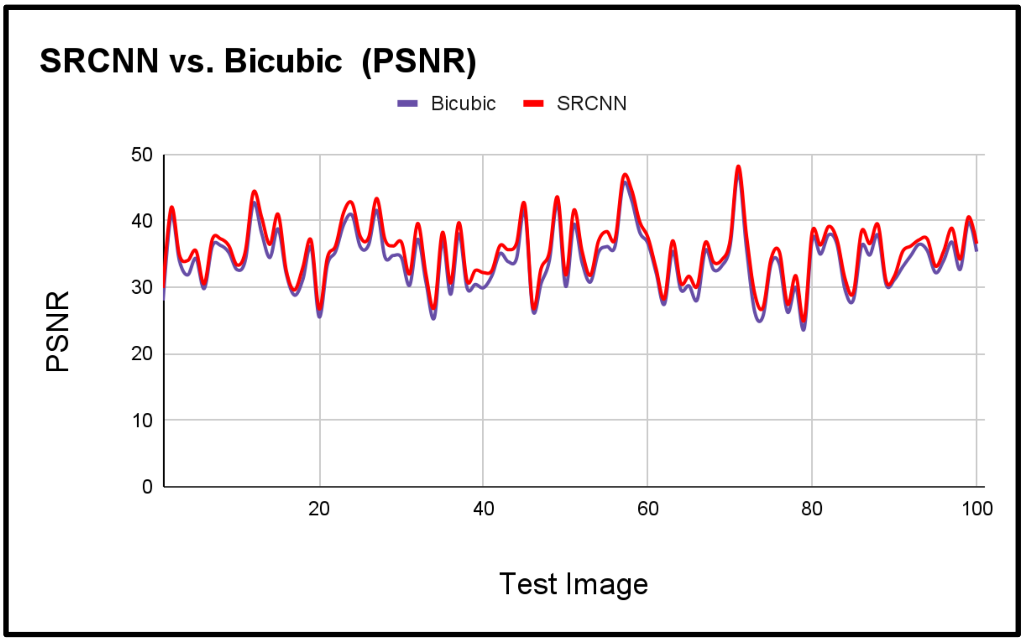


Fig 3.PSNR Comparison of Bicubic Interpolation and SRCNN

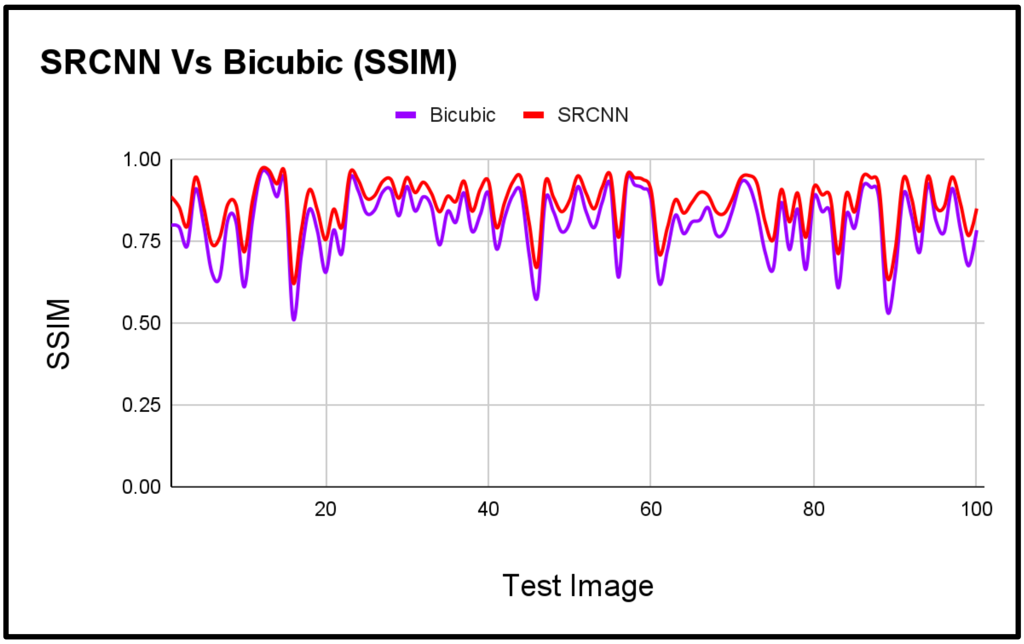


Fig 4.SSIM Comparison of Bicubic Interpolation and SRCNN

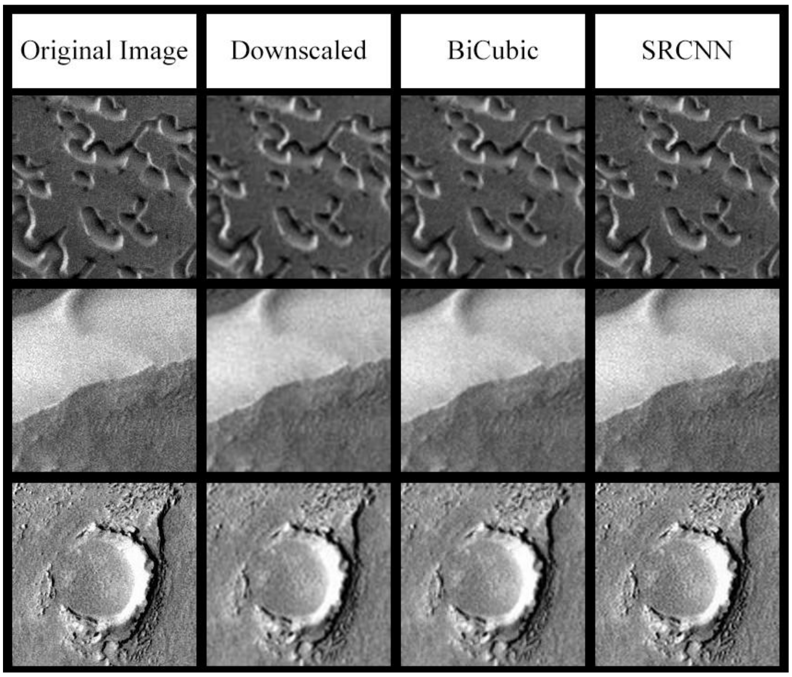


Fig. 5. Comparison of original, downgraded, Bicubic and SRCNN images

## IV. CONCLUSION

In conclusion we were able to study the performance of SRCNN on satellite images of Mars and were able to show that the model performs much better than bicubic interpolation by as much as 1dB. We were also able to show how the images generated by SRCNN are much more perceptually similar to the original images than standard interpolation. With vast amounts of research being conducted into the possible colonization of Mars, it is important for researchers to obtain as much information as they can about the planet, remotely from Earth before a single person is sent to the planet. Super Resolution of satellite images can help researchers obtain more accurate and voluminous insight about the planet, in fields such as landform classification, spectral analysis for mineral detection etc.

## REFERENCES

[1]. W. Yang, X. Zhang, Y. Tian, W. Wang, J. Xue, and Q. Liao, Deep Learning for Single Image Super-Resolution: A Brief Review, in *IEEE Transactions on Multimedia, vol. 21, no. 12, pp. 3106-3121*

[2]. S. Anwar, S. Khan, and N. Barnes, A Deep Journey into Super-resolution, *ACM Computing Surveys, vol. 53, no. 3. Association for Computing Machinery (ACM), pp. 1–34, May 31, 2021.*

[3]. M. U. Müller, N. Ekhtiari, R. M. Almeida, and C. Rieke, Super-Resolution Of Multispectral Satellite Images Using Convolutional Neural Networks, *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. V-1–2020. Copernicus GmbH, pp. 33–40, Aug. 03, 2020.*

[4]. C. Dong, C. C. Loy, K. He, and X. Tang, Learning a Deep Convolutional Network for Image Super-Resolution, *Computer Vision – ECCV 2014. Springer International Publishing, pp. 184–199, 2014.*

[5]. M. Lin, Q. Chen, and S. Yan, Network In Network. *arXiv, 2013.*

[6]. T. Wilhelm et al., DoMars16k: A Diverse Dataset for Weakly Supervised Geomorphologic Analysis on Mars, *Remote Sensing, vol. 12, no. 23. MDPI AG, p. 3981, Dec. 04, 2020.*

A.G. Manish. "Super-Resolution of Mars Satellite Images Using Convolutional Neural Networks." *International Journal of Engineering Science Invention (IJESI)*, Vol. 11(06), 2022, PP 01-06. Journal DOI- 10.35629/6734