Super-Resolution of Advanced Himawari Imager Data Using SRCNN

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Abstract: This study applies the Super-Resolution Convolutional Neural Network (SRCNN) to Advanced Himawari Imager (AHI) data to enhance spatial resolution. Six spectral bands were analysed: B01, B02, B04 B05, B06, and B15. High-resolution images were downsampled to generate low-resolution counterparts, and LR–HR tile pairs were used for training. Evaluation with PSNR, SSIM, brightness, contrast, and local contrast indicated considerable improvements for 1 km bands (B01, B02, and B04), while 2 km bands (B05, B06, and B15) showed limited enhancement.

Keywords: CNN-based super resolution, image quality evaluation, spectral band

1. Introduction

High-resolution satellite imagery plays an essential role in weather monitoring, disaster assessment, and environmental studies. The Himawari-8 geostationary satellite, operated by the Japan Meteorological Agency, provides continuous multi-spectral observations over the Asia-Pacific region. However, spatial resolution varies across spectral bands: visible channels such as B01, B02 and B04 are available at 1 km, while other important channels such as B05, B06, and B15 are restricted to 2 km. Band 03, on the other hand, is provided at 500 m, the highest spatial resolution among AHI bands. Since the objective of this study is to harmonize bands with lower resolutions to higher ones, Band 03 does not require further super-resolution processing and is therefore excluded from analysis.
This resolution gap limits applications requiring finer detail. Super-resolution (SR) techniques based on deep learning offer a potential solution. SRCNN (Dong 2016) is one of the earliest convolutional neural network models for SR and provides a useful baseline for evaluating feasibility on satellite data. This study investigates the effectiveness of SRCNN for Himawari AHI imagery across six spectral bands and analyses its performance through quantitative and qualitative evaluations.

2. Methodology

This study used Himawari AHI data acquired on May 2, 2023. Six bands were selected: three with 1 km resolution (B01, B02, and B04) and three with 2 km resolution (B05, B06, and B15). Outline of the method is shown in Figure 1. High-resolution (HR) images were downsampled by a factor of two to create low-resolution (LR) counterparts, and LR–HR pairs were generated. The HR images were divided into 100 × 100-pixel tiles and the LR images into 50 × 50-pixel tiles. Only tiles containing land areas were selected to construct the dataset.

SRCNN with a three-layer architecture was employed, consisting of feature extraction, non-linear mapping, and reconstruction layers. Each band was trained independently, with radiometric normalization applied to account for differences in band characteristics. Training used mean squared error (MSE) loss and the Adam optimization method.

For evaluation, Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) were used to assess fidelity and structural consistency. In addition, local contrast was introduced to examine texture preservation and fine-detail reconstruction. Evaluations were conducted on central subregions to eliminate the influence of boundary artifacts.

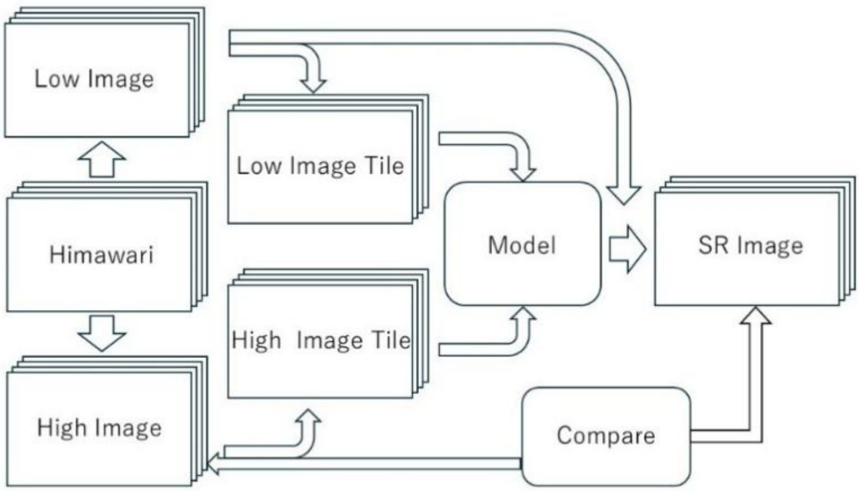

Figure 1: Research flow

3. Results/Findings

Figure 2 presents visual comparisons of LR, HR, and SR images for the six analysed bands. For the 1 km bands (B01, B02, B04), SR images clearly show enhanced details compared to LR, particularly in cloud edges, coastlines, and land surface textures. These improvements bring the SR results closer to HR references, demonstrating that SRCNN successfully restored fine spatial structures. In contrast, for the 2 km bands (B05, B06, B15), improvements are less pronounced. While some localized structures appear sharper, overall textures remain blurred compared to HR, highlighting the difficulty of recovering fine details from inherently coarse-resolution bands.

Table 1 summarizes the quantitative evaluation results. For B01, B02, and B04, both PSNR and SSIM values improved, confirming that SRCNN enhanced fidelity and structural similarity. However, for B05, B06, and B15, PSNR and SSIM values decreased compared to LR, suggesting that SRCNN was less effective for bands with inherently coarse resolution.

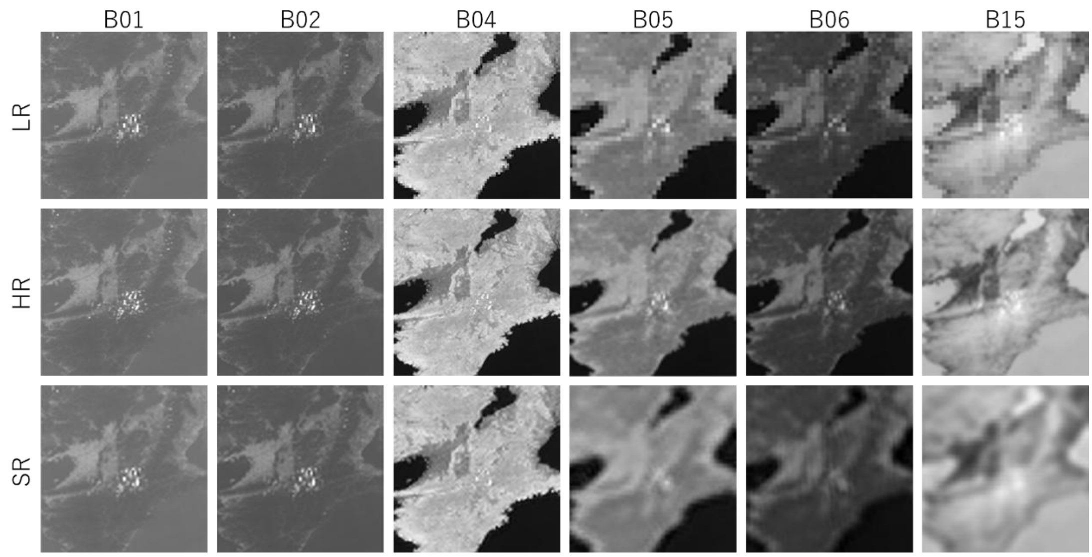

Figure 2: Example of low resolution, high resolution and super resolution image

Local contrast values were generally lower for SR images than for LR images. Several factors explain this outcome. First, SRCNN is trained to minimize mean squared error (MSE), which favours smoother outputs and suppresses local brightness variations. Second, LR images may exhibit artificially high local contrast due to noise or aliasing introduced during downsampling. Third, preprocessing steps such as interpolation and normalization can suppress contrast in SR outputs. Finally, the evaluation window size influences results: larger windows average out fine details, penalizing smooth SR reconstructions while favouring the grainy appearance of LR images.

Table 1: Comparison of PSNR, SSIM and contrast

(a) PSNR

	B01	B02	B04	B05	B06	B15
LR	41.9	42.0	38.5	41.5	43.3	42.5
SR	43.8	44.1	40.3	40.0	42.5	42.3

(b) SSIM

	B01	B02	B04	B05	B06	B15
LR	0.981	0.982	0.961	0.971	0.977	0.979
SR	0.958	0.960	0.930	0.889	0.909	0.948

(c) RMS contrast

	B01	B02	B04	B05	B06	B15
LR	0.0092	0.0090	0.015	0.013	0.010	0.017
HR	0.0093	0.0092	0.016	0.013	0.010	0.017
SR	0.0086	0.0086	0.014	0.011	0.009	0.016

These findings demonstrate that SRCNN is effective for bands where LR retains sufficient high-frequency information (1 km bands), but its performance declines for bands with inherently low spatial resolution (2 km bands). This suggests the necessity of more advanced SR models or band-aware approaches to improve results in such cases.

4. Conclusion

SRCNN successfully improved Himawari AHI imagery for 1 km bands but provided limited enhancement for 2 km bands. These results highlight both the potential and limitations of CNN-based SR. Future work will investigate advanced architectures, multi-band learning strategies, and larger training datasets to expand the applicability of SR for operational meteorology and disaster monitoring.

Acknowledgement

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References

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