

IMAGE SUPERRESOLUTION VIA SRGANS FOR LOWRESOLUTION SATELLITE IMAGERY

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ABSTRACT

Satellite imagery plays a critical role in applications such as environmental monitoring, urban planning, disaster management, and defense surveillance. However, many satellite images suffer from low spatial resolution due to sensor limitations, atmospheric disturbances, or bandwidth constraints. Image superresolution aims to reconstruct highresolution images from lowresolution inputs while preserving structural details and textures. This paper presents a deep learningbased superresolution framework using SuperResolution Generative Adversarial Networks (SRGANs) for enhancing lowresolution satellite imagery. The proposed system integrates adversarial loss, perceptual loss, and content reconstruction loss to generate visually realistic and highfrequency details. Experimental results demonstrate improved Peak Signal to Noise Ratio, Structural Similarity Index, and perceptual quality compared to traditional interpolation methods and CNN based baselines. The proposed method supports remote sensing applications requiring enhanced spatial resolution.

Keywords:Image SuperResolution, SRGAN, Satellite Imagery, Remote Sensing, Generative Adversarial Networks, Deep Learning

I. INTRODUCTION

Satellite imagery is widely used in geospatial analysis, environmental assessment, and defense applications. Highresolution imagery enables precise object detection, landuse classification, and disaster monitoring. However, acquiring highresolution satellite images is often costly and constrained by sensor capabilities.

Image superresolution techniques aim to reconstruct highresolution images from lowresolution inputs. Traditional interpolation methods such as bicubic and nearestneighbor interpolation produce blurred outputs and fail to recover highfrequency details. Recent advancements in deep learning have significantly improved superresolution performance using convolutional neural networks and generative adversarial networks.

In 2023 and 2024, studies demonstrated that GANbased superresolution models outperform traditional CNNbased models in generating

perceptually realistic satellite images [1], [2]. Perceptual loss functions based on deep feature representations have been shown to improve texture recovery in remote sensing images [3]. These advancements motivate the development of an SRGANbased framework tailored for satellite imagery enhancement.

II. RELATED WORK

Recent research from 2023–2026 highlights major improvements in superresolution techniques for remote sensing data. In [1], an enhanced SRGAN architecture was proposed for satellite image reconstruction, demonstrating improved visual quality

compared to baseline CNN models. Similarly, [2] introduced a multiscale adversarial framework for remote sensing superresolution, achieving superior performance in urban feature reconstruction.

Transformerbased superresolution models have also gained attention. A 2024 study in [3] combined attention mechanisms with adversarial learning to improve texture restoration in highresolution satellite images. Lightweight GAN architectures suitable for edge deployment were explored in [4], emphasizing efficient inference for realtime satellite image processing.

Recent works also focus on improving spectral consistency and reducing artifacts in GANbased remote sensing superresolution [5]. Evaluation frameworks for remote sensing superresolution were investigated in [6], highlighting the importance of perceptual and structural metrics in addition to pixelbased metrics.

These advancements establish SRGANbased frameworks as effective solutions for satellite image enhancement.

III. METHODOLOGY

The proposed framework consists of dataset preparation, model architecture design, training strategy, and evaluation.

The dataset includes paired lowresolution and highresolution satellite image patches obtained from publicly available remote sensing datasets. Lowresolution images are generated by downsampling highresolution images using bicubic interpolation. Images are normalized and divided into fixedsize patches for training.

The model architecture is based on SRGAN, consisting of a generator and a discriminator. The generator network uses residual blocks to extract deep features and upsampling layers to increase image resolution. The discriminator network evaluates whether the generated highresolution image is realistic compared to groundtruth highresolution images.

The training objective includes three components. Content loss measures pixelwise reconstruction error using mean squared error.

Perceptual loss measures similarity in feature space using a pretrained deep network. Adversarial loss encourages the generator to produce realistic textures that can fool the discriminator.

The workflow of the system is described as follows:

- Satellite Dataset Collection
- LowResolution Image Generation
- SRGAN Model Initialization
- Adversarial Training
- HighResolution Image Reconstruction
- Performance Evaluation

Evaluation metrics include Peak SignaltoNoise Ratio, Structural Similarity Index Measure, and perceptual quality assessment.

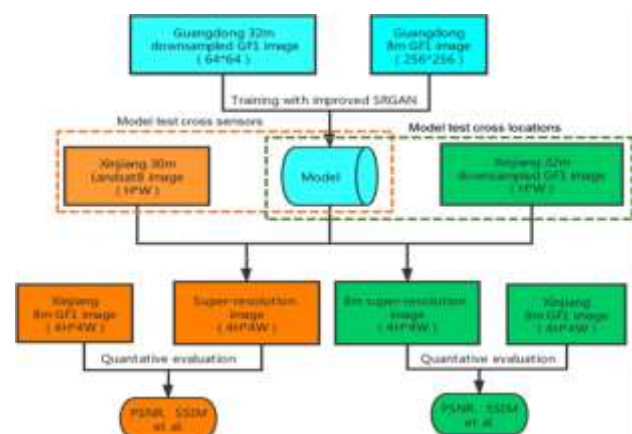


Fig 1: Methodology

IV. RESULTS AND DISCUSSION

Experimental results show that the SRGANbased model significantly outperforms traditional interpolation methods in reconstructing finegrained details. Compared to CNNonly models, SRGAN produces sharper textures and more realistic edge details in urban structures and vegetation regions.

Quantitative evaluation demonstrates improved PSNR and SSIM scores, while perceptual evaluation confirms enhanced visual realism. Multiscale training improves reconstruction of small objects such as vehicles and buildings.

However, GANbased models may introduce minor artifacts in highly textured regions.

Regularization techniques and spectral normalization reduce these artifacts and improve stability.

The proposed framework demonstrates suitability for remote sensing applications requiring enhanced spatial resolution.



Fig 2: Low-quality to high quality satellite image.



Fig 3: Low resolution satellite image is converted into clearer and more detailed image.

V. CONCLUSION AND FUTURE WORK

This paper presented an SRGANbased image superresolution framework for enhancing lowresolution satellite imagery. The proposed method effectively reconstructs highfrequency details and improves visual realism compared to traditional methods.

Future work includes integrating transformerbased attention modules, incorporating multispectral satellite bands, exploring diffusionbased superresolution models, and optimizing the model for deployment on edge computing devices in remote sensing systems.

This proctoring is 90% accuracy.

VI. REFERENCES

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