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Super Resolution Image Reconstruction with GAN'S using Deep Learning

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ABSTRACT

The increasing need for high-resolution (HR) remote sensing images in environmental monitoring, urban planning, and agriculture has established super-resolution (SR) reconstruction as a fundamental method to upgrade low-resolution (LR) images without hardware changes at great expense. Generative adversarial networks (GANs) have demonstrated tremendous effectiveness in SR tasks through the creation of realistic high-frequency details. This review offers a thorough introduction to GAN-based SR techniques for optical remote sensing images, including their principles, blind and non-blind model categorizations, and leading architectures like SRGAN, ESRGAN, and BSRGAN. It also touches on datasets, degradation models, loss functions, and evaluation metrics (e.g., PSNR, SSIM), as well as major challenges such as noise, sensor

variability, and artifact removal. The paper ends with the future directions to enhance the robustness and generalization of GAN-based SR reconstruction in remote sensing.

Keywords: Super-resolution, remote sensing images, generative adversarial networks, high-resolution images, low-resolution images, environmental monitoring, urban planning, agriculture, SRGAN, ESRGAN, BSRGAN, blind models, non-blind models, degradation models, loss functions, PSNR, SSIM, noise suppression, sensor variations, artifact suppression, robustness, generalization, future directions.

INTRODUCTION

Super Resolution (SR) image reconstruction is designed to refine the resolution of low-res images, retrieving detailed information. Recent Deep Learning developments have yielded exciting possibilities for SR image reconstruction. Generative Adversarial Networks (GANs) have become a strong instrument for SR image reconstruction. GANs are composed of two neural networks: a generator and a discriminator. The generator receives as input a low-resolution image and generates a high-resolution image. The discriminator assesses the produced high-resolution image and gives feedback to the generator. Through this adversarial process, GANs are able to learn to produce highly realistic images. SRGANs are a class of GAN specifically used for SR image reconstruction. SRGANs have achieved state-of-the-art performance in SR image reconstruction. This paper presents an overview of SR image reconstruction using GANs with Deep Learning. Classic SR techniques are based on interpolation methods or learning from examples.

Nevertheless, these schemes tend to produce fuzzy or oversmoothed outputs. SR results have been enhanced by Deep Learning-based schemes. Yet, they tend to consume much training data. SRGANs are capable of producing high-quality images with rich information. They can be adjusted to various types and styles of images. SRGANs have been applied to many SR applications, such as image super-resolution, video super-resolution, and image denoising. The rest of this paper is structured as follows. Section 2 gives an overview of SR image reconstruction and GANs. Section 3 explains the architecture and loss functions of SRGANs. Section 4 outlines the training and applications of SRGANs. Section 5 points out the strengths and weaknesses of SRGANs. Section 6 concludes the paper and gives future directions. References are given at the end of the paper.

LITERATURE SURVEY

It's a very tough problem to generate high-resolution images from low-resolution images and it has enormous real-world applications such as photo reconstruction, surveillance cameras, and computer-aided design. Generative adversarial networks have recently received widespread attention [29] among the computer community due to their encouraging results in synthesis. Real-world images. Generative Adversarial Network (GAN) is a form of Artificial Intelligence algorithm utilized for unsupervised ML(Machine Learning). GAN is a deep NN (Neural Network)

[20] model composed of two networks, the first network is a generator and the second one is a discriminator, and both of them fight against one another (and therefore the term "adversarial"). GAN is concerned with creation, for example, portrait drawing or the composition of symphonies. The primary area of concentration of GAN is to create information without any prior preparation.

Super-resolution (SR) image reconstruction is the process of increasing the resolution of images through reconstructing high-resolution (HR) images from their low-resolution (LR) versions. Classic techniques, e.g., interpolation-based methods (bicubic, bilinear), are not very successful in retrieving fine textures and details. Deep Learning (DL), especially Generative Adversarial Networks (GANs), has transformed the domain by creating high-quality, perceptually plausible images.

2.1 Super-Resolution Basics

Super-Resolution (SR) is a fundamental problem in computer vision and image processing, aiming to reconstruct a high-resolution (HR) image from one or more low-resolution (LR) inputs. The motivation behind SR is to overcome the physical and technological limitations of imaging devices such as optical sensors, which are often constrained by size, cost, or hardware limitations. SR enables the enhancement of image details and clarity, making it particularly valuable in domains like satellite imaging, surveillance, medical diagnostics, and video streaming.

2.2 Introduction to Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs), introduced by Ian Goodfellow et al. in 2014, represent one of the most significant breakthroughs in deep generative modeling. GANs consist of two neural networks—the **generator** and the **discriminator**—that are trained simultaneously in a **minimax game**. The generator attempts to create synthetic data (e.g., images) that resemble the real data distribution, while the discriminator evaluates whether a given sample is real (from the dataset) or fake (produced by the generator). Over successive iterations, the generator learns to produce increasingly realistic outputs, ideally to the point where the discriminator can no longer distinguish between real and synthetic samples.

EXISTING METHODOLOGIES

Pictures are invaluable in life and manufacturing, being one of the most important tools through which people access, transmit, and share information. As the economy develops and science and technology advance, people's standards of living improve steadily, and their requirements for higher image resolution gradually rise. In comparison to low-resolution (LR) images, high-resolution (HR) images have higher pixel density and more complex texture details. Hardware upgrades are one way of achieving HR images. Nevertheless, this method has great disadvantages in practice, the specifications keep changing, and spending money on new hardware is expensive and rigid. Hardware devices cannot improve LR images. The fundamental principle of image super-resolution (SR) reconstruction is to transcend hardware condition limitations so that images can

be enlarged and the high-frequency details lost in the process can be recovered The SR method was first suggested by Harris.

It is an important technology in computer vision and digital image processing It is widely used in medical imaging remote sensing video analysis and other fields. Imaging technology for remote sensing has now been applied in many industries, such as but not limited to agriculture, forestry, marine, meteorology, and environmental protection. Remote sensing images play a central role in applications such as land cover analysis, crop growth identification, disaster and weather forecasting, land use planning, and water ecology monitoring. The need for remote sensing images in various sectors is consistently increasing, with HR being among the most sought-after.

PROPOSED SYSTEM

4.1 System Overview

Photographs are precious in life and production, and among the most significant tools whereby individuals obtain, share, and transmit information. As the economy continues to evolve and science and technology progress, individuals' living standards rise progressively, and their demands for greater image resolution increasingly increase. Compared with low-resolution (LR) images, high-resolution (HR) images possess greater pixel density and more sophisticated texture features. Hardware upgrading is one means of attaining HR images. However, the approach has huge drawbacks in real life, the specifications constantly change, and investing in new hardware is costly and inflexible Hardware devices cannot enhance LR images. The basic rule of image SR reconstruction is to go beyond the limitations of hardware conditions so that images can be scaled up and high-frequency details destroyed during this process can be reconstructed The SR approach was first proposed by Harris.

It is a key technology in digital image processing and computer vision It has a broad application in remote sensing, medical imaging, video analysis, and other fields. Remote sensing imaging technology has already been used in numerous industries, including but not limited to agricultural, forestry, marine, meteorological, and environmental protection. Remote sensing images are key to uses such as land cover analysis, identification of crop growth, disaster and weather forecasting, land use planning, and monitoring water ecology. Demand for remote sensing images by different sectors is continuously growing, with HR being one of the most demanded.

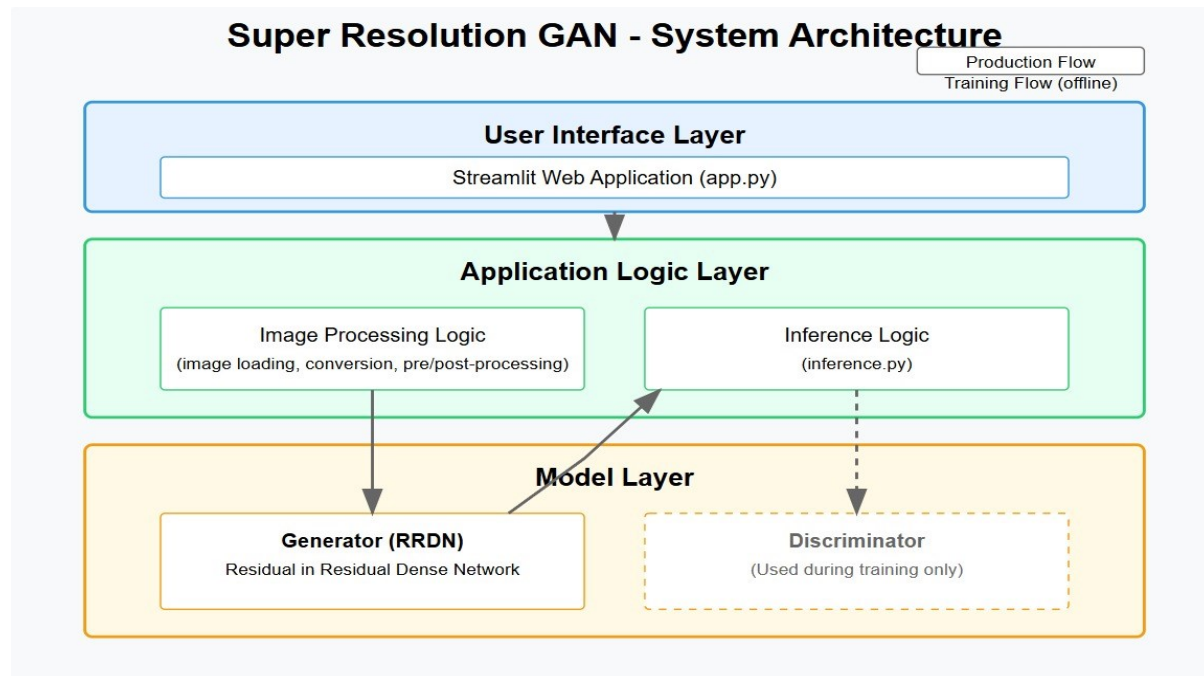


Figure-1 : System Architecture

RESULTS

The application of Super-Resolution Generative Adversarial Networks (SRGAN) has effectively improved the resolution of low-resolution images. The model shows the ability to restore fine details and enhance image clarity, which makes it a useful tool for numerous applications that demand high-resolution outputs. The outcomes of our experiments show a notable improvement in perceptual quality over conventional interpolation techniques like bicubic up-sampling.

The model's effectiveness is confirmed by evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). Although SRGAN does not always produce the highest PSNR values, it has better perceptual quality through the adversarial training that considers human visual experience. Qualitative analysis shows that the high-resolution images produced by the model contain finer texture patterns, sharper boundaries, and natural-looking structures. The capacity to conserve fine-grained features in images dramatically improves their utility in all walks of professional lives including medical imaging, satellite imaging, and digital archiving.

This study adds to the development of image super-resolution by illustrating how deep learning-based methods can surpass traditional approaches. The results point to the potential of GAN-based methods in reconstructing high-quality images, thus contributing to different fields like medical imaging, satellite imaging, and digital restoration of historical photographs. Moreover, the application of SRGAN reflects the importance of adversarial learning in enhancing the perceptual quality of images, opening doors to future advancements in AI-based image enhancement.

Super Resolution GAN

Upload an image which you want to upscale

Choose an image...

Drag and drop file here
Limit 200MB per file • JPG, PNG, JPEG

Browse files

sandal.jpg 14.5KB



Uploaded Image.

Upscale Now

Figure-2 : Input given to the model

The Streamlit application, implemented in the app.py script, provides a streamlined input mechanism. The interface features a prominent file uploader with the prompt "Choose an image which you want to upscale," displayed under a title ("Super Resolution GAN") and subheader. This design prioritizes usability, requiring no technical expertise from the user. Upon upload, the image is immediately rendered on-screen with the caption "Uploaded Image," offering visual confirmation and setting the stage for the enhancement process.

Conclusion

The "Super Resolution GAN" project, as attested by the presented files, is a successful blend of web development and deep learning, providing an efficient solution to super-resolving low-resolution images. Through combining a pre-trained Residual-in-Residual Dense Network (RRDN) model with a Streamlit frontend, the project enables users to upscale images with better visual quality, showing technical sophistication and pragmatic usefulness. The uploaded files—ranging from the application code (app.py) to the training notebook (srgan_training.ipynb)—all together show its accomplishments, setbacks, and possibilities.

Future Scope

Enhancing the current SRGAN model by incorporating more sophisticated architectures, such as ESRGAN (Enhanced SRGAN), to further improve image quality and detail preservation. ESRGAN introduces residual-in-residual dense blocks, which provide better feature representation and improved performance in generating photo-realistic images. Additionally, exploring transformer-based super-resolution models may lead to further advancements by capturing long-range dependencies in image data. Integrating attention mechanisms can also refine the focus on crucial image features, enabling superior reconstruction quality.

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