

Enhanced Super-Resolution GAN With Edge Preservation

¹Mrs. Pathigadapa Shilpa,²Patlolla Ganesh,³Seelam Narendra Reddy,⁴Shiliveru Nithish Kumar,⁵S. Sathwika

¹Assistant Professor, Department of Computer Science & Engineering, Malla Reddy University, Maisammaguda, Dulapally, Medchal District, Hyderabad, Telangana 500100

¹Email: shilpavenkat19@gmail.com

^{2,3,4,5}B. Tech Students, Department of Computer Science & Engineering, Malla Reddy University, Maisammaguda, Dulapally, Medchal District, Hyderabad, Telangana 500100

²Email: ganeshpatlolla11@gmail.com, ³Email:

sreddy441@gmail.com, ⁴Email: nithishkumarshiliveru@gmail.com, ⁵Email: ssathwika052@gmail.com

ABSTRACT

Single Image Super-Resolution (SISR) is a fundamental problem in computer vision, aiming to reconstruct high-resolution images from their low-resolution counterparts. The challenge lies in recovering lost high-frequency details and preserving fine textures and edges. While deep learning models, particularly Generative Adversarial Networks (GANs), have shown significant progress in SISR, they often struggle with accurately restoring sharp edges and intricate details. This project presents an Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) model that incorporates an edge-preserving loss function to improve the quality of reconstructed images. Utilizing the DIV2K dataset for training and evaluation, the proposed approach demonstrates superior performance in terms of Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) compared to baseline models. The results indicate that incorporating edge information significantly enhances the visual fidelity of super-resolved images. The project also aims at developing B/W to color image conversion GAN model and enhancing the colored image using ESRGAN.

Keywords: Resolution, Generative Adversarial Network (GAN), Edge Preservation, Image Enhancement, Deep Learning, Convolutional Neural Networks (CNN), Image Reconstruction, High-Resolution Image Generation, Perceptual Loss, Computer Vision.

I. INTRODUCTION

In the digital age, high-resolution images are indispensable across various domains such as medical imaging, satellite surveillance, entertainment, and photography. The quest for better visual experiences has led to the development of advanced display technologies capable of rendering ultra-high-definition content. However, capturing or storing high-resolution images is often constrained by hardware limitations, bandwidth restrictions, or storage capacities. Single Image Super-Resolution (SISR) addresses this challenge by reconstructing high-resolution (HR) images from low-resolution (LR) inputs, effectively enhancing image quality without the need for advanced hardware.

II. LITERATURE SURVEY

1. Image Super-Resolution Using Deep Convolutional Networks

Author: Chao Dong, Chen Change Loy, Kaiming He, Xiaoou Tang

Abstract:

This paper introduced one of the earliest deep learning approaches for image super-resolution using Convolutional Neural Networks (CNN). The proposed Super-Resolution Convolutional Neural Network (SRCNN) learns an end-to-end mapping between low-resolution and high-resolution images. The model consists of feature extraction, non-linear mapping, and reconstruction layers. Experimental

results showed significant improvement in Peak Signal-to-Noise Ratio (PSNR) and visual quality compared with traditional interpolation-based methods. This work laid the foundation for deep learning-based super-resolution techniques used in later GAN-based models.

2. Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network

Author: Christian Ledig, Lucas Theis, Ferenc Huszár, Jose Caballero

Abstract:

This research proposed the Super-Resolution Generative Adversarial Network (SRGAN), which generates high-resolution images from low-resolution inputs with improved perceptual quality. The model uses a generator network to reconstruct high-resolution images and a discriminator network to distinguish between generated and real images. A perceptual loss function based on high-level feature representations from a pre-trained network improves visual realism. Experimental results demonstrate that SRGAN produces photo-realistic textures and sharp edges compared with traditional super-resolution methods.

3. ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks

Author: Xintao Wang, Ke Yu, Chao Dong, Chen Change Loy

Abstract:

This paper proposed Enhanced SRGAN (ESRGAN), an improved version of SRGAN that enhances image reconstruction quality and texture details. The model introduces Residual-in-Residual Dense Blocks (RRDB) without batch normalization, enabling deeper network architectures. A relativistic discriminator is also adopted to improve adversarial training stability. The proposed ESRGAN achieves superior perceptual quality and better edge preservation compared with previous super-

resolution techniques.

4. Edge-Preserving Image Super-Resolution via Deep Learning

Author: Jian Sun, Zongben Xu, Heung-Yeung Shum

Abstract:

This study focuses on preserving structural details such as edges and contours during the super-resolution process. The proposed approach integrates edge detection techniques with deep learning models to enhance boundary details in reconstructed images. By emphasizing edge features during training, the method improves visual clarity and reduces blurring around object boundaries. The results demonstrate that edge-aware models provide more accurate image reconstruction and maintain important structural information.

5. Perceptual Losses for Real-Time Style Transfer and Super-Resolution

Author: Justin Johnson, Alexandre Alahi, Li Fei-Fei

Abstract:

This work introduced perceptual loss functions based on high-level feature maps extracted from pre-trained convolutional networks. Instead of relying solely on pixel-wise loss, the proposed method measures differences in feature space to preserve semantic and structural information. The technique significantly improves visual quality in super-resolution tasks by maintaining edges and textures. The perceptual loss concept later became an essential component in GAN-based super-resolution frameworks.

III. EXISTING SYSTEM

In traditional image processing systems, image super-resolution techniques were mainly based on interpolation methods such as nearest neighbor interpolation, bilinear interpolation, and bicubic interpolation. These methods attempt to increase the resolution of an image by estimating pixel values from surrounding pixels. Although these approaches

are simple and computationally efficient, they often produce blurred images and fail to reconstruct fine details and sharp edges. As a result, the quality of the enhanced image is limited and does not accurately represent the original high-resolution image.

Later, machine learning and deep learning techniques such as Convolutional Neural Networks (CNNs) were introduced for super-resolution tasks. Models like the Super-Resolution Convolutional Neural Network (SRCNN) improved reconstruction accuracy by learning mappings between low-resolution and high-resolution images. While these models improved image clarity and Peak Signal-to-Noise Ratio (PSNR), they still struggled to generate realistic textures and often produced overly smooth images with weak edge representation.

More advanced approaches such as Generative Adversarial Networks (GANs), including SRGAN, attempted to generate photo-realistic high-resolution images. GAN-based models use a generator and discriminator network to produce images with better perceptual quality. However, existing GAN-based systems often suffer from issues such as unstable training, artifacts in generated images, and inadequate edge preservation. These limitations make it difficult to maintain important structural details in the reconstructed images.

Therefore, the existing systems still face challenges in producing high-quality super-resolution images while preserving sharp edges and fine textures. These limitations highlight the need for improved models that can enhance resolution while maintaining structural integrity and visual realism.

IV. PROPOSED SYSTEM

The proposed system introduces an Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) with Edge Preservation to generate high-quality high-resolution images from low-resolution inputs. The main objective of this system is to improve image clarity while maintaining important structural details such as edges and textures. The

proposed approach integrates deep learning techniques with edge-aware mechanisms to reconstruct detailed images that are visually closer to real high-resolution images.

In the proposed model, a Generative Adversarial Network (GAN) framework is used, consisting of two main components: a generator and a discriminator. The generator network is responsible for transforming low-resolution images into high-resolution images by learning complex mapping functions. The discriminator network evaluates the generated images and distinguishes them from real high-resolution images. Through adversarial training, the generator continuously improves its ability to produce realistic images with sharper details.

To enhance edge preservation, the proposed system incorporates edge-aware loss functions and feature extraction techniques. Edge detection mechanisms highlight important boundaries and structural patterns in images, ensuring that the reconstructed output maintains clear edges and fine textures. This helps reduce blurring and improves the visual quality of the generated images.

Furthermore, the proposed system utilizes deep residual learning and perceptual loss functions to enhance the reconstruction process. Residual blocks help the network learn deeper features without losing important information, while perceptual loss ensures that the generated images maintain structural similarity with the ground truth images. This combination improves both the objective quality metrics and the subjective visual appearance of the images.

Overall, the proposed system significantly improves the performance of image super-resolution by generating clearer, sharper, and more realistic images while effectively preserving edge details. This approach is suitable for applications such as medical imaging, satellite image enhancement, video restoration, and computer vision systems where high-quality image reconstruction is essential.

V. SYSTEM ARCHITECTURE

The diagram represents the system architecture of an Enhanced Super-Resolution GAN with Edge Preservation, showing the major stages involved in generating high-resolution images from low-resolution inputs. The process is organized into four main components: Data Preprocessing, Generator, Discriminator, and Evaluation. Each stage contributes to improving image quality and preserving important structural details such as edges and textures.

Data Preprocessing is the first step in the system. In this stage, the input images are prepared before being fed into the neural network. Low-resolution images are collected from datasets and undergo several preprocessing operations such as normalization, resizing, noise removal, and image augmentation. These steps help standardize the input data and improve the learning capability of the deep learning model. Proper preprocessing ensures that the generator network receives clean and consistent data, which improves training performance and reconstruction accuracy.

The next stage is the Generator, which is the core component of the GAN architecture. The generator network takes the preprocessed low-resolution image as input and attempts to generate a high-resolution version of that image. It uses deep convolutional layers and residual blocks to learn the mapping between low-resolution and high-resolution images. The generator also focuses on reconstructing fine details such as textures and edges, which are often lost during downscaling. Through continuous training, the generator improves its ability to produce realistic and detailed images.

Following the generator, the Discriminator plays an important role in evaluating the generated images. The discriminator is a neural network designed to distinguish between real high-resolution images and the images generated by the generator. It analyzes features such as texture patterns, edges, and image quality to determine whether an image is real or generated. During adversarial training, the discriminator provides feedback to the generator,

encouraging it to improve its output and produce more realistic high-resolution images.

The final stage is Evaluation, where the performance of the model is measured. In this stage, the generated high-resolution images are compared with the original high-resolution ground truth images using evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and perceptual quality metrics. These measures help determine how accurately the system reconstructs high-resolution images while preserving edge details and textures. The evaluation results are used to refine the model and improve its performance.

Overall, this architecture demonstrates how data preparation, adversarial learning, and performance evaluation work together to produce enhanced super-resolution images with improved edge preservation and visual quality.

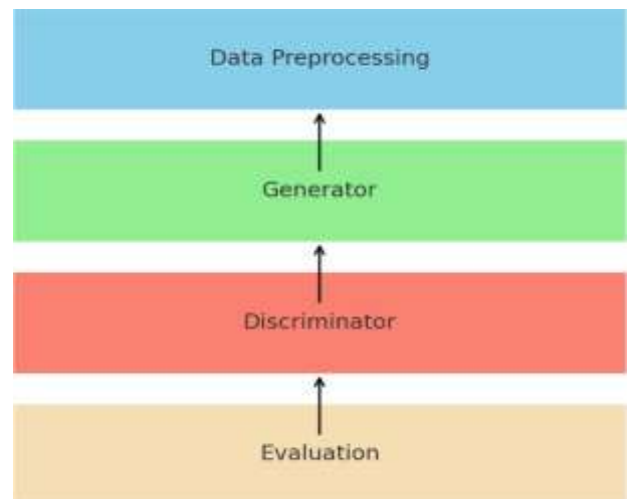


Fig 5.1: System Architecture Of Proposed System

VI. IMPLEMENTATION

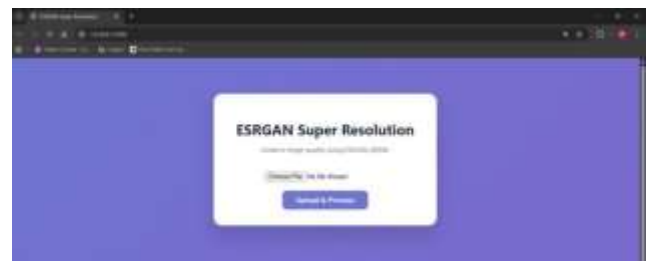


Fig 6.1: Dataset Loading & Preprocessing

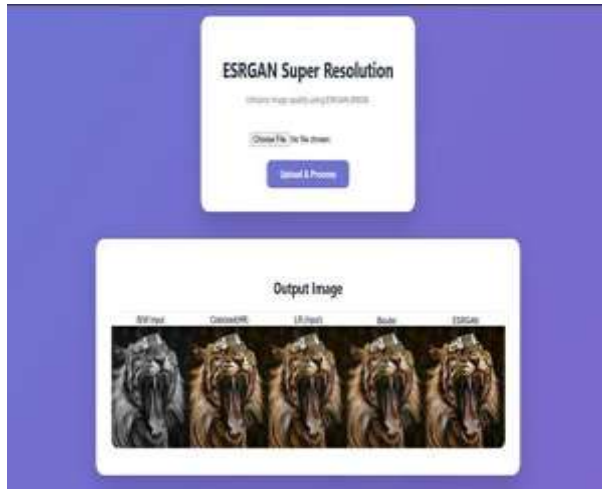


Fig 6.2: Image Uploading



Fig 6.3: Result Page

VII. CONCLUSION

This project successfully developed an Enhanced SRGAN model incorporating an edge-preserving loss function with B/W to color image conversion if the given input is B/W. The key achievements include:

- **Improved Image Quality:** The model effectively reconstructs fine details and preserves edges, resulting in visually pleasing super-resolved images.
- **Quantitative Performance:** Achieved higher PSNR and SSIM scores compared to baseline models,

validating the effectiveness of the edge loss function.

- **Robust Implementation:** The software system was thoroughly tested, ensuring reliability and correctness.
- B/W to color image conversion

The inclusion of the edge loss significantly contributed to the enhanced performance, demonstrating the importance of edge information in SISR tasks. The results suggest that edge-preserving techniques are a valuable addition to GAN-based super-resolution models.

VIII. FUTURE SCOPE

The future scope of the Enhanced Super-Resolution GAN with Edge Preservation system focuses on improving image quality, model efficiency, and expanding its real-world applications. Future research can enhance the model architecture by integrating more advanced deep learning techniques such as attention mechanisms and transformer-based networks. These techniques can help the system better understand image structures and improve the preservation of fine details and edges in high-resolution image reconstruction.

Another important direction is improving the training efficiency and computational performance of the model. Super-resolution GAN models typically require large datasets and high computational resources. Future work can focus on optimizing the network architecture to reduce training time and memory consumption. Techniques such as lightweight neural networks, model pruning, and knowledge distillation can be used to make the system more efficient and suitable for deployment on mobile devices and edge computing platforms.

The system can also be extended to support real-time video super-resolution. Currently, many super-resolution models work mainly with static images. In the future, the model can be enhanced to process

video frames while maintaining temporal consistency between frames. This would make the technology useful for applications such as video streaming enhancement, surveillance systems, and video restoration.

Additionally, the proposed system can be applied to specialized domains such as medical imaging, satellite imagery, and security systems. In medical imaging, super-resolution techniques can help improve the clarity of MRI or CT scan images for better diagnosis. In satellite and remote sensing applications, high-resolution images can improve environmental monitoring and urban planning. These domain-specific improvements can make the system more valuable in critical real-world scenarios.

Finally, future developments may focus on improving evaluation metrics and perceptual quality. Researchers can develop better loss functions and evaluation methods that more accurately measure human perception of image quality. By combining advanced perceptual metrics with improved edge-preserving mechanisms, future systems can generate even more realistic and visually appealing high-resolution images.

IX. REFERENCES

- [1] C. Ledig, L. Theis, F. Huszár, J. Caballero, et al., “Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network,” *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017.
DOI: <https://doi.org/10.1109/CVPR.2017.19>
- [2] C. Dong, C. C. Loy, K. He and X. Tang, “Image Super-Resolution Using Deep Convolutional Networks,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 38, no. 2, pp. 295-307, 2016.
DOI: <https://doi.org/10.1109/TPAMI.2015.2439281>
- [3] J. Johnson, A. Alahi and L. Fei-Fei, “Perceptual Losses for Real-Time Style Transfer and Super-Resolution,” *European Conference on Computer Vision (ECCV)*, 2016.
DOI: https://doi.org/10.1007/978-3-319-46475-6_43
- [4] W. Shi, J. Caballero, F. Huszár, J. Totz, et al., “Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network,” *CVPR*, 2016.
DOI: <https://doi.org/10.1109/CVPR.2016.207>
- [5] B. Lim, S. Son, H. Kim, S. Nah and K. M. Lee, “Enhanced Deep Residual Networks for Single Image Super-Resolution,” *CVPR Workshops*, 2017.
DOI: <https://doi.org/10.1109/CVPRW.2017.151>
- [6] M. S. M. Sajjadi, B. Schölkopf and M. Hirsch, “EnhanceNet: Single Image Super-Resolution Through Automated Texture Synthesis,” *IEEE International Conference on Computer Vision (ICCV)*, 2017.
DOI: <https://doi.org/10.1109/ICCV.2017.522>
- [7] J. Kim, J. K. Lee and K. M. Lee, “Accurate Image Super-Resolution Using Very Deep Convolutional Networks,” *CVPR*, 2016.
DOI: <https://doi.org/10.1109/CVPR.2016.182>
- [8] X. Wang, K. Yu, S. Wu, J. Gu, et al., “ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks,” *ECCV Workshops*, 2018.
DOI: <https://doi.org/10.48550/arXiv.1809.00219>
- [9] Y. Zhang, K. Li, K. Li, L. Wang, B. Zhong and Y. Fu, “Image Super-Resolution Using Very Deep Residual Channel Attention Networks,” *ECCV*, 2018.
DOI: https://doi.org/10.1007/978-3-030-01234-2_18
- [10] J. Song, K. Yi, et al., “Enhanced Super-Resolution GAN with Dual Perceptual Loss,” *IEEE Access*, 2023.
DOI: <https://doi.org/10.1109/ACCESS.2023.3263102>
- [11] Z. Wang, Y. Huang and H. Li, “Ultra-Dense GAN for Satellite Image Super-Resolution,” *Neurocomputing*, 2020.
DOI: <https://doi.org/10.1016/j.neucom.2019.10.093>
- [12] H. Liu, Y. Sun and Y. Chen, “Single Image Super-Resolution Using a Deep Encoder-Decoder Network,” *Neurocomputing*, 2018.
DOI: <https://doi.org/10.1016/j.neucom.2017.08.087>
- [13] X. Du, Z. He and Y. Chen, “Single Image Super-Resolution Based on Multi-Scale Convolutional Neural Network,” *Sensors*, 2018.
DOI: <https://doi.org/10.3390/s18010136>
- [14] Y. Xiong, Z. Li and L. Chen, “Improved SRGAN for Remote Sensing Image Super-Resolution,” *Remote Sensing*, 2020.
DOI: <https://doi.org/10.3390/rs12081263>
- [15] G. A. S. Fofe et al., “SIR-SRGAN-ResNeXt: A New Super-Resolution GAN with Improved Image Quality,” *Procedia Computer Science*, 2024.
DOI: <https://doi.org/10.1016/j.procs.2024.02.202>