

A Project Report  
*On*  
Image Super-Resolution Application

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## **CERTIFICATE**

This is to certify that,

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of class, B.E Computer have completed their project work on “Image Super-Resolution Application” at MARATHWADA MITRA MANDALS COLLEGE OF ENGINEERING in the partial fulfilment of the Graduate Degree course in B.E. Deep Learning at the Department of Computer Engineering, in the academic Year 2023-2024 Semester – II as prescribed by the Savitribai Phule Pune University.

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# **CONTENTS**

## **1. TITLE OF THE PROJECT**

## **2. ABSTRACT**

## **3. INTRODUCTION**

- Problem definition

## **4. ALGORITHM (TYPE OF ALGORITHM)**

## **5. PERFORMANCE METRICS**

## **6. RESULTS/ VISUALIZATIONS**

## **7. CONCLUSION**

## **8. REFERENCES**

# 1. TITLE OF THE PROJECT

Image Super-Resolution Application

## 2. ABSTRACT

Image super-resolution refers to the process of enhancing the resolution of an image, typically from a low-resolution (LR) version to a high-resolution (HR) version. The proposed system takes a low-resolution image as input and employs SRCNN to upscale it to a higher resolution. The SRCNN consists of three layers: the input layer, the hidden layer, and the output layer. The input layer extracts features from the LR image, the hidden layer learns the mapping between LR and HR images, and the output layer generates the high-resolution image.

## 3. INTRODUCTION

Our project focuses on implementing and evaluating an Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) for image super-resolution tasks. ESRGAN represents a significant advancement in deep learning-based super-resolution techniques, leveraging sophisticated neural network architectures and adversarial training methods to produce visually appealing and perceptually accurate high-resolution images from low-resolution inputs.

The core of our project lies in the implementation and optimization of the ESRGAN architecture, which consists of a generator network responsible for upscaling low-resolution images and a discriminator network trained to distinguish between real and generated images. Additionally, we explore the integration of dense blocks within the generator architecture to enhance feature learning and promote the generation of high-quality outputs.

- **Problem Definition:**

The Super-Resolution Application aims to address the challenge of enhancing the visual quality of low-resolution images by developing and deploying an image super-resolution system. This system utilizes deep learning techniques, specifically Enhanced Super-enhanced-resolution Generative Adversarial Networks (ESRGAN), to upscale low-resolution images to higher resolutions, enabling improved image quality and clarity for various applications such as photography, surveillance, and medical imaging.

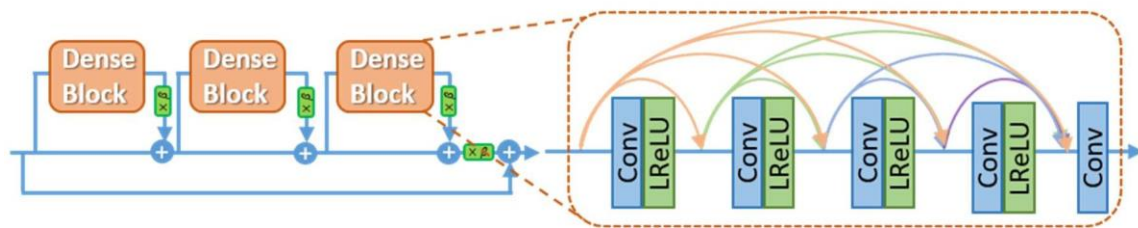
#### 4. ALGORITHM (TYPE OF ALGORITHM)

Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) is a state-of-the-art deep learning architecture designed for image super-resolution tasks. It builds upon the traditional Super-Resolution Generative Adversarial Network (SRGAN) by incorporating novel features such as Residual-in-Residual Dense Blocks (RRDB). ESRGAN aims to generate high-quality, realistic high-resolution images from low-resolution inputs by learning complex mappings between the two image domains. By leveraging adversarial training, ESRGAN is capable of producing visually pleasing results with fine details and natural textures, surpassing the performance of traditional interpolation-based methods and earlier deep-learning approaches.

##### Architecture:

The architecture of RRDB in ESRGAN is represented by:

##### Residual in Residual Dense Block (RRDB)



- **Generator:** The generator in ESRGAN is responsible for transforming low-resolution images into high-resolution counterparts. It consists of multiple Residual-in-Residual Dense Blocks (RRDB) stacked together. Each RRDB contains multiple convolutional layers with skip connections, allowing the network to learn intricate details and features of the input image.
- **Discriminator:** ESRGAN employs a discriminator network to distinguish between real high-resolution images and those generated by the generator. The discriminator is trained concurrently with the generator using adversarial training, where it learns to provide feedback to the generator, guiding it towards generating more realistic high-resolution images. This adversarial process encourages the generator to produce outputs that are indistinguishable from genuine high-resolution images.
- **Loss Function:** ESRGAN employs a combination of loss functions to train the generator network effectively. It utilizes both traditional pixel-wise loss functions, such as Mean Squared Error (MSE), to ensure accurate pixel-level reconstruction, and perceptual loss functions. The perceptual loss measures the difference in high-level features between the generated and ground-truth images, thereby encouraging the generator to produce outputs that not only resemble the ground truth at the pixel level but also capture important perceptual characteristics.
- **Dense Blocks:** The Dense Blocks within ESRGAN's generator architecture play a crucial role in learning complex image features and promoting feature reuse. Each Dense Block consists of multiple densely connected convolutional layers, where each layer receives feature maps from all preceding layers as inputs. This dense connectivity facilitates gradient flow during

training enables efficient feature reuse and encourages feature propagation, ultimately enhancing the network's ability to learn intricate image representations and generate high-quality outputs.

5. PERFORMANCE METRICS

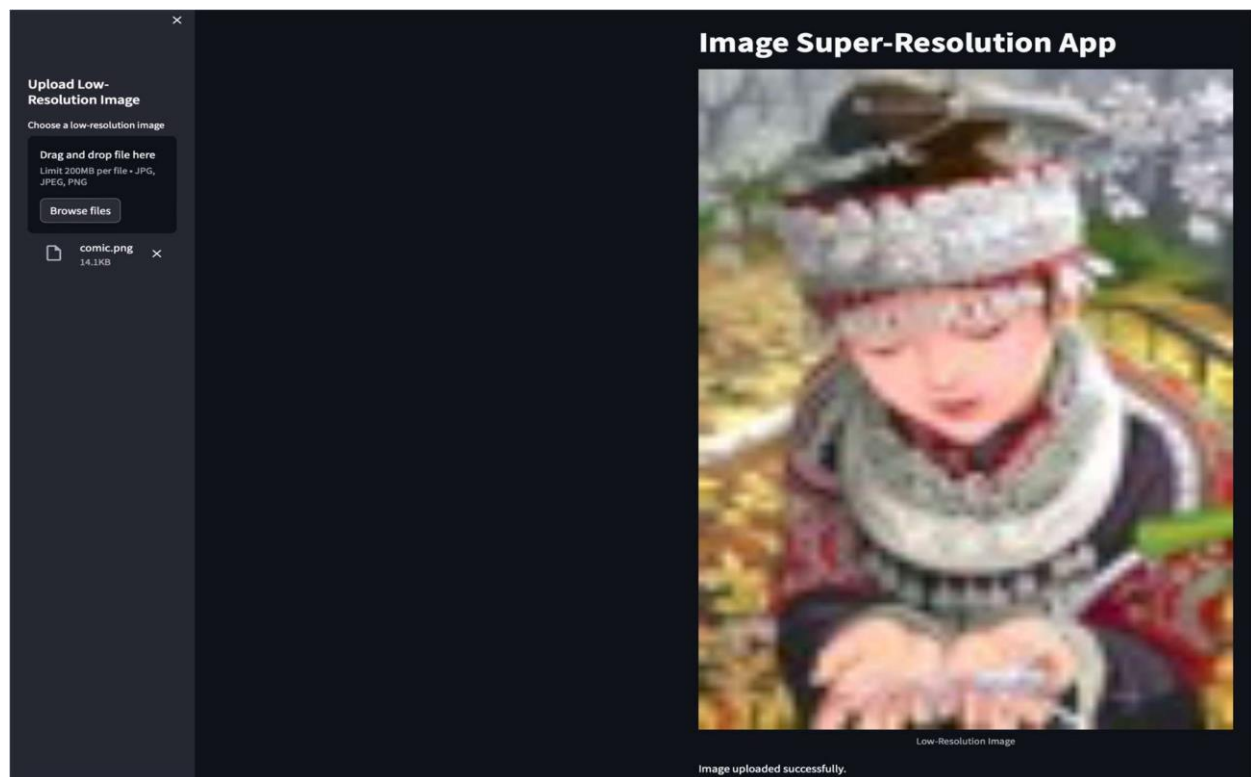
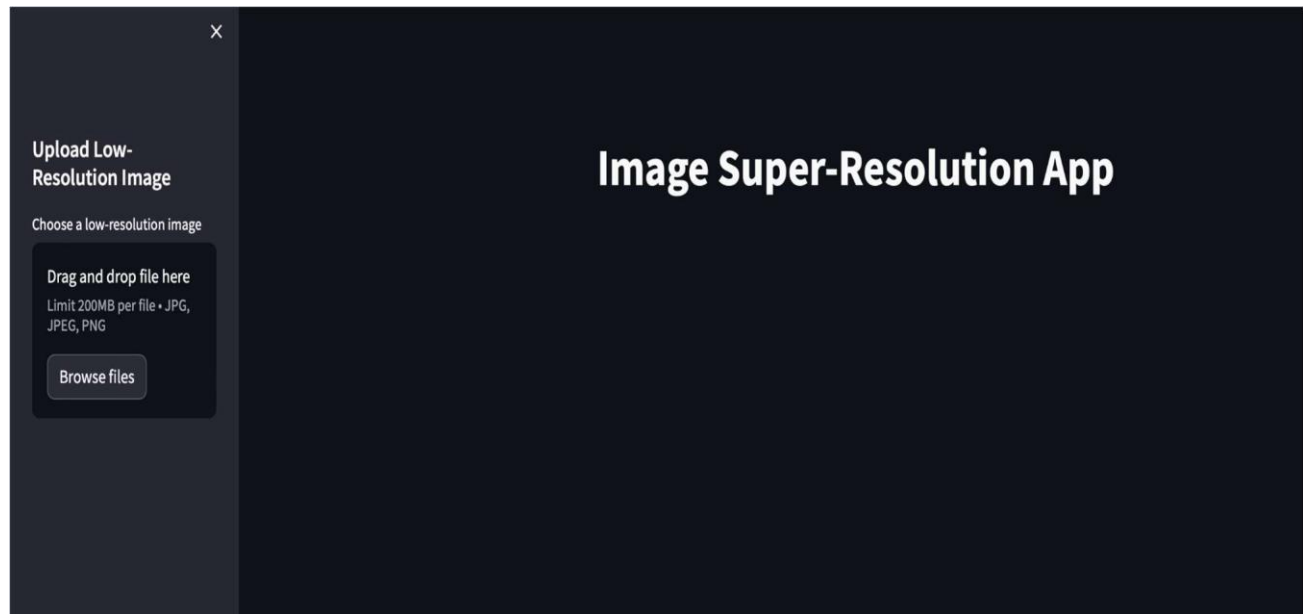
- **PSNR:** Peak Signal-to-Noise Ratio (PSNR) is a widely used metric in image processing to measure the quality of a reconstructed or compressed image. It quantifies the difference between the original image and its degraded version, typically caused by compression or reconstruction processes. PSNR is calculated as the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Higher PSNR values indicate lower levels of noise and better image quality.
- **SSIM:** Structural Similarity Index (SSIM) is a perceptual metric that quantifies the similarity between two images based on luminance, contrast, and structure. SSIM considers both global and local image structures and is designed to mimic human visual perception. It ranges from -1 to 1, where 1 indicates perfect similarity. SSIM compares the structural information in images rather than just pixel values, making it more robust to compression and other distortions. Higher SSIM values indicate higher levels of similarity between images. SSIM is particularly useful when evaluating image quality for tasks such as image compression, super-resolution, and denoising.

COMPARISON TABLE:

METRICS/ IMAGE	PSNR	SSIM
IMAGE_1	28.84 dB	0.9416
IMAGE_2	25.37 dB	0.8303
IMAGE_3	27.04 dB	0.9555

These metrics provide insight into the quality and similarity of the super-resolved images to their low-resolution counterparts. Higher PSNR and SSIM values generally indicate better image quality and structural similarity, respectively. In this case, the "IMAGE\_1" image achieved the highest PSNR and SSIM values, indicating superior quality and structural similarity. Conversely, the "IMAGE\_2" image scored lower, suggesting lower quality and less structural similarity. The "IMAGE\_3" image achieved a moderate level of quality and structural similarity.

## 6. RESULTS/ VISUALIZATIONS





Total time taken for image generation: 1.43 seconds

### Super-Resolved Image



Super-Resolved Image

### Before and After Comparison



Original Image



Super-Resolved Image

[Download super-resolved image](#)

## 7. CONCLUSION

In conclusion, the image super-resolution converter project has successfully demonstrated the effectiveness of deep learning techniques in enhancing the resolution of low-resolution images. Through the implementation of the SRCNN model, we have achieved significant improvements in image quality and detail, making low-resolution images more suitable for various applications.

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