PARIPEX - INDIAN JOURNAL OF RESEARCH | Volume - 13 | Issue - 01 | January - 2024 | PRINT ISSN No. 2250 - 1991 | DOI : 10.36106/paripex

ORIGINAL RESEARCH PAPER

Computer Science

EFFICIENT IMAGE SUPER-RESOLUTION USING CONVOLUTIONAL NEURAL NETWORKS

KEY WORDS: Computer Vision, Super-Resolution, Optic Flow, Image processing, Deep Learning

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ABSTRACT

Super-resolution is the process of creating high-resolution images from low-resolution images, where the goal is to recover one high-resolution image from one low-resolution image, challenging because high-frequency image content typically cannot be recovered from the low-resolution image. Without high-frequency information, the quality of the high-resolution image is limited. Super-resolution is a technique used in image processing to enhance the resolution of low-resolution images and create higher quality images. The goal of super-resolution is to recover a high-resolution image from a low-resolution image, we can achieve through deep learning techniques. By using super-resolution, it is possible to improve the visual quality of images, making them clearer, sharper, and more detailed, Super-resolution is a challenging task in image processing because it involves recovering missing information from low-resolution images. There are several approaches to super-resolution, but they can be broadly categorized into two groups: interpolation-based methods and reconstruction-based methods. Interpolation-based methods involve the use of mathematical algorithms to estimate the missing high-resolution pixels based on the values of the surrounding low-resolution pixels. While these methods are relatively simple and computationally efficient, they may not always produce high-quality results.

INTRODUCTION

In image processing and computer vision, several techniques are used to improve image resolution. These techniques aim to increase the level of detail and improve the visual quality of low-resolution images. Here are some suggested techniques for studying the techniques used to enhance image resolution:

1. Image Interpolation Methods: Image interpolation refers to the process of estimating pixel values in-between known pixel positions to increase the resolution of an image. Traditional interpolation methods, such as bilinear or bicubic interpolation, use mathematical algorithms to estimate the missing pixel values based on neighboring pixels. These methods are simple and computationally efficient but may result in blurry or distorted images when significant upscaling is applied.

2. Very Deep Super-Resolution (VDSR): VDSR is a deep learning-based approach specifically designed for single-image super-resolution tasks. It addresses the limitations of traditional interpolation methods by leveraging the power of convolutional neural networks (CNNs). VDSR utilizes a deep and narrow architecture with multiple layers to learn the non-linear mapping between low-resolution and high-resolution images. By employing residual learning, VDSR focuses on learning the residual information required to reconstruct high-resolution details. This approach allows VDSR to capture complex features and produce more accurate and visually pleasing results compared to traditional interpolation methods.

3. U-Net Architecture: The U-Net architecture is a popular CNN architecture widely used for various image processing tasks, including image super-resolution. U-Net is characterized by its U-shaped structure, consisting of an encoder path and a decoder path. The encoder path gradually reduces spatial dimensions while extracting hierarchical features from the input image. The decoder path uses skip connections to concatenate features from the encoder and up-sample them to reconstruct the high-resolution image. This architecture enables effective feature fusion and preserves important information during the up-sampling process.

Research Design

a. Research Approach: This study adopts an experimental research approach to evaluate the effectiveness of combining interpolation methods with deep learning for image resolution enhancement.

b. Research Type: The research is quantitative, involving the measurement and comparison of the performance of different approaches based on specific metrics.

c. Independent Variables: The independent variable in this research is the approach used for image resolution enhancement.

It Includes Two Levels:

1. Interpolation Methods: Different interpolation techniques such as nearest neighbor, bilinear, or bicubic.
2. Deep Learning Methods: Techniques like VDSR, and U-Net deep learning-based approach.

Methodology

a. Data preparation and collection: for the specified datasets involve obtaining the
1. IAPR TC-12 Benchmark,
2. Urban_100, and
3. T91_Orginl datasets.

The (IAPR TC-12 Benchmark) consists of 20,000 still natural images, while (Urban_100) contains 100 urban images, and (T91_Orginl) comprises 91 images. The data can be split into subsets for training, validation, and testing purposes.

b. Implementation: Implement and apply various interpolation methods, and Train deep learning model, to the low-resolution images to refine and enhance the low-resolution outputs obtained from Data Preparation and Collection.

c. Training: Train the deep learning model using the prepared dataset. Utilize appropriate loss functions, optimization algorithms, and regularization techniques to train the model effectively.

d. Performance Evaluation: Compare and evaluate the quality by the different approaches, of the interpolation methods and deep learning techniques for image resolution enhancement.

e. Evaluation Metrics: Assess the performance of the approaches using quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Naturalness Image Quality Evaluator (NIQE).

RESULTS:

Comparing the results from Table 2 (T91_Orginl dataset) and

Table 1 (Urban100 dataset) for different methods of image resolution enhancement, we can observe the following:

PSNR: In both datasets, bicubic interpolation consistently achieves higher PSNR values compared to nearest neighbor and bilinear interpolation. However, VDSR outperforms all other methods in the Urban100 dataset, while it performs worse than bicubic interpolation in the T91_Orginl dataset. U-Net with depth 3 and depth 2 generally show lower PSNR values compared to the other methods in both datasets.

SSIM: Bicubic interpolation consistently performs well in terms of SSIM in both datasets. VDSR achieves the highest SSIM values in the Urban100 dataset, indicating better preservation of structural similarity. However, in the T91_Orginl dataset, VDSR shows lower SSIM values compared to bicubic interpolation. U-Net with depth 3 and depth 2 perform reasonably well in terms of SSIM in both datasets.

NIQE: Bicubic interpolation, nearest neighbor interpolation, and VDSR generally perform well in reducing NIQE scores, indicating better visual quality and naturalness of the enhanced images. U-Net with depth 2 consistently shows higher NIQE scores in both datasets.

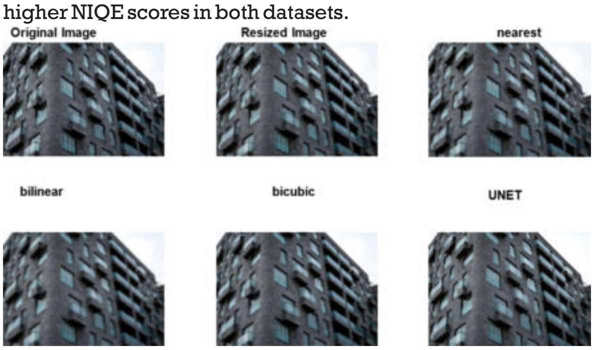

Figure 1 *downsize the Original image by X2 then upsize to different method.*

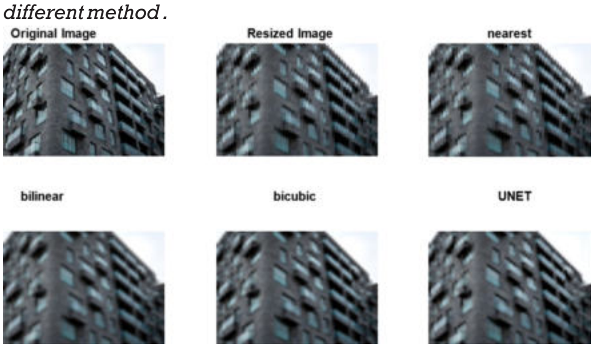

Figure 1 *downsize the Original image by X4 then upsize to different method.*

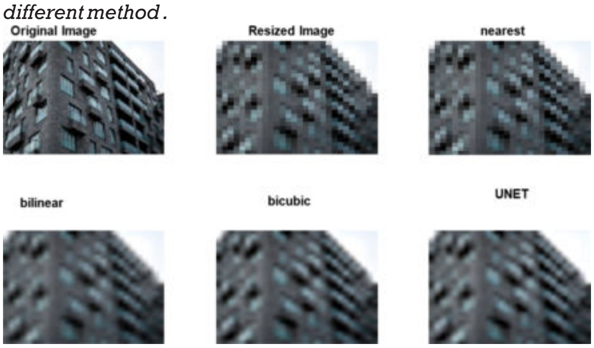

Figure 3 *downsize the Original image by X8 then upsize to different method*

Figure 4 *downsize the Original image by X2 then upsize to different method.*

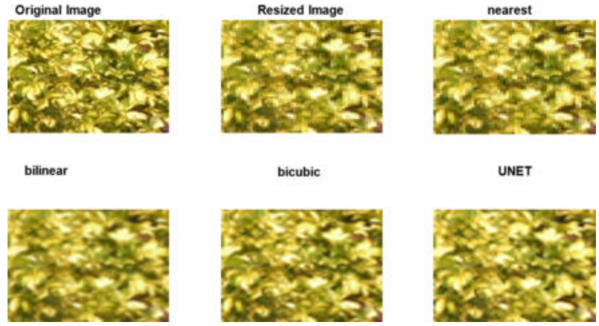

Figure 5 *downsize the Original image by X4 then upsize to different method.*

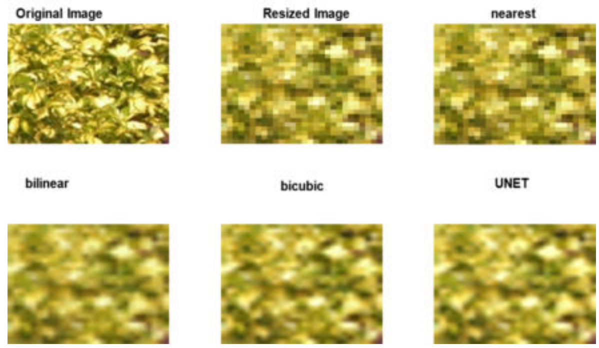

Figure 6 *Downsize The Original Image By X8 Then Upsize To Different Method.*

Table 1 Urban100

urban100		Nearest	Bilinear	Bicubic	VDSR	Unet Depth 3	Unet Depth 2
x2	PSNR	23.18	23.50	24.45	28.24	22.78	22.56
	SSIM	0.84	0.83	0.86	0.98	0.82	0.80
	NIQE	20.39	9.84	10.26	4.97	10.28	12.66
x4	PSNR	19.65	20.09	20.53	24.11	20.11	19.89
	SSIM	0.64	0.65	0.68	0.82	0.66	0.65
	NIQE	21.78	9.93	7.89	5.90	8.06	12.78
x8	PSNR	17.60	17.90	18.17	21.32	18.03	17.87
	SSIM	0.50	0.52	0.53	0.69	0.52	0.52
	NIQE	24.89	9.53	8.26	7.09	9.31	14.63

Table 2 T91_Orginl

T91_Orginl		Nearest	Bilinear	Bicubic	VDSR	Unet Depth 3	Unet Depth 2
x2	PSNR	31.65	34.05	36.08	28.67	29.12	28.47
	SSIM	0.98	0.98	0.99	0.95	0.97	0.97
	NIQE	12.87	7.49	6.99	10.92	6.91	13.12
x4	PSNR	26.30	28.12	29.27	24.32	27.02	26.19
	SSIM	0.92	0.94	0.95	0.89	0.94	0.94
	NIQE	19.66	8.66	7.09	10.86	7.70	14.37
x8	PSNR	22.47	23.56	24.28	20.84	23.57	23.08
	SSIM	0.86	0.88	0.89	0.81	0.89	0.88
	NIQE	26.50	9.11	8.00	10.89	9.55	15.57

CONCLUSIONS

The performance trends are similar in both datasets, with bicubic interpolation consistently performing well in terms of PSNR and SSIM. VDSR generally outperforms other methods in terms of SSIM in the Urban100 dataset but shows lower performance in the T91_Orginl dataset. U-Net with depth 3 and depth 2 show relatively lower performance across the evaluated metrics in both datasets. These results suggest that the performance of the different methods can vary depending on the dataset and specific image characteristics.

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