Single Image Super Resolution using Enhanced Deep Residual Networks

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Abstract

Low-resolution and low-quality images pose significant difficulties in visual object recognition problems essential to surveillance and navigation in a variety of military and civilian use cases. The signal to noise ratio (SNR) and mean square error (MSE) metrics of the super-resolved image have improved significantly as a result of recent advancements in deep learning-based techniques like Enhanced Deep Super Resolution network (EDSR) and Very Deep Super Resolution (VDSR). However, there may not be a direct correlation between these pixel domain signal quality metrics and machine vision tasks like object recognition and key point detection. A super-resolution technique that improves gradient images and associated features from low-resolution images for the benefit of high-level machine vision tasks is the focus of this work. With scale space adaptive network depth, a residual learning deep neural network-based gradient image super-resolution solution is developed here. Simulation results demonstrate performance gains in key points repeatability and gradient image quality.

Keywords—*Image Resolution, Deep Residual Network, Deep Convolutional Neural Networks*

I. Introduction

.One of the huge challenges in image recognition is dealing with low resolution images. Especially, in military and surveillance applications, recognition is done from low quality input images. However, if the image is captured from a further distance, the quality remains very low and unrecognizable which is actually a great concern in some sectors e.g. Department of Defense (DoD) while dealing with counter Unmanned Aircraft System (UAS) . One of the popular solutions in this case would be image super-resolution. Super-resolution [1] means finding a mapping from the low-resolution (LR) image to its high-resolution (HR) version. In the case of single frame super resolution (SISR), the number of pixels for a single image is increased so that it can visually look better as well as can be efficacious while recognition. However, in addition to super-resolving the image, the key concern is to preserve the features so that it can be recognized accurately. Nowadays, image SR is driven by the emergence of deep learning methods. Recently, numerous deep learning based super-resolution methods have been introduced. In [2], SRCNN method is established which is an end to end system between the input low-resolution images and its interpolated high-resolution images. The results exhibit quite a good gain over the other methods. In [3], VDSR method is established which generates a very deep convolutional neural network(CNN) with stages of small filters resulting in faster convergence and much gain in PSNR. In [4], the proposed enhanced deep learning based super-resolution (EDSR) method is further replicated in stages to finally produce the deep layers of super-resolution network being inspired from residual network. In typical super-resolution methods, the goal is to improve peak signal to noise ratio(PSNR). But, from the practical point of view, these SR methods generate more eye-soothing high-quality image by increasing PSNR which eventually contribute towards losing key features. So, while identifying those images, we need to preserve the important local and global features e.g. recognizing captured low quality images from surveillance cameras using their features or identifying an aircraft using key feature points in Air Force. There are quite a few works on low-resolution image recognition. In [5], very low-resolution recognition (VLRR) problem has been dealt with deep learning based model for demonstrating the task with face recognition, font recognition, digit recognition. In [6], another deep CNN based method is proposed to deal with face and other objects with low quality. In many recognition tasks, gradient images are important information derived from pixel images. To define, gradient image generally refers to a change in the direction of the intensity or color of an image. Numerous works regarding image recognition have been done using gradient of images. In [7] and [8], Harris Detector and Laplacian of Gaussian are used to find out the features of edges and corners and blobs of an image respectively. In [9], SIFT feature detection is used which discovers local features after computing maxima and minima from the Difference of Gaussian(DoG) image set. In recognition, key points from an object are extracted to provide a description of the features which are used for recognizing the object. So, it should be important to keep in mind that extracted features should be able to be used in case of scale, noise and illumination changes. SIFT can handle these change making SIFT an ideal method for feature extraction. There is few research regarding the preservation of features. In [10], a visual query compression for preserving local features is introduced. Here, they go through a new method in visual key points compression which uses subspaces for optimization of preserving key point feature matching properties than the reconstruction performance. Our proposed method in this paper is not an end to end system. Rather, it is a super-resolving network which generates SIFT repeatability. So the objective is to super-resolve the images in gradient domain so that it preserves SIFT features which will eventually contribute for better recognition. Our SR network is constructed.

II. LITERATURE REVIEW

The related work section discusses various aspects of technology in image resolution enhancement models:

In a study by W. Siu, K. Hung et al., image interpolation and super-resolution techniques are examined. Aimed at enhancing image and video quality for applications like HDTV and face recognition, the research reviews various interpolation methods and introduces novel approaches such as non-local means for hole filling in 3D video synthesis. Emerging trends and directions in the field are also discussed.[1]

In a research conducted by J. Kim, J.K. Lee, K.M. Lee et al., an advanced super-resolution technique using deep reconstruction networks is introduced. By augmenting a deep reconstruction network with the VGG network, they achieve significantly improved accuracy. Their approach efficiently utilizes relevant information in large image regions and provides a simple yet robust training framework, resulting in faster convergence rates compared to previous methods. Overall, their method surpasses existing techniques in terms of accuracy and demonstrates substantial improvements in image quality.[3]

In an exploration by Lim P., Melody S., Kim H., Nah S., Lee K.M. et al. introduced the Enhanced Deep Super-Resolution (EDSR) framework, surpassing existing super-resolution techniques. By optimizing residual blocks and employing enhanced training strategies, their model achieves significant performance improvements. They also propose a novel multi-layered high-resolution approach, outperforming contemporary methods and winning the NTIRE2017 Super-Resolution Challenge.[4]

III. SYSTEM ANALYSIS

3.1.EXISTING METHOD

The existing system provides solution for the enhancing the resolution of single images. The approach employs a deep convolutional network inspired by VGG-net, known for ImageNet classification. Increasing the depth of our network significantly improves accuracy, and the final model incorporates 20 weight layers. To efficiently leverage contextual information across large image regions, this process cascade small filters multiple times within our deep network structure. However, training very deep networks poses a challenge to convergence speed. We propose a simple yet effective training procedure to address this issue.

3.2.ADVANTAGES

- It produces a stable error gradient and a stable convergence.
- Improved clarity
- Enhanced Analysis
- Enhanced Data Visualization

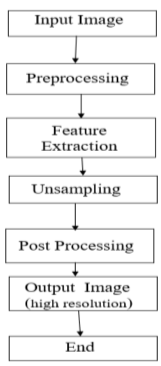
3.3.DISADVANTAGES

- Poor perceptual quality.
- Lack high frequency content, realistic textures and are perceived blurry.

3.4.PROPOSED SYSTEM

The proposed approach involves a deep learning pipeline designed for image super resolution. Unlike an end-to-end system, our network aims to achieve SIFT repeatability. Instead of utilizing a high-resolution image in the pixel domain, we create a super-resolved Gaussian blurred image with various standard deviations. The concept is to generate high-resolution gradient images from the Gaussian blurred image and subsequently integrate them with SIFT to preserve matching points. Typically, gradient images are formed by convolving the original image with a filter. Our image gradient method is inspired by the SIFT technique, where various Gaussian blurred images with different standard deviations are initially generated from an input image.

3.5.PROJECT FLOW



SYSTEM REQUIREMENTS:

A software program requirements specification (SRS) is an outline of an evolving software program machine. It determines the functional and non-purposeful necessities and can consist of a hard and fast of user cases that describe the user enjoy the software should provide. The necessities are indexed and divided into person necessities, device necessities and useful requirements. Gathering software program necessities from the client, reading and documenting them is known as requirements engineering. The motive of the requirements engineer is to create and maintain a complex and descriptive system necessities specification document.

- Inspection of present or legacy systems and software
- Smartphones and builders.
- Accessing the database or
- Collect responses from questionnaires

SOFTWARE REQUIREMENTS

Operating System: Windows 7/8/10
Server-side Script: HTML, CSS, Bootstrap & JS
Programming Language: Python
Libraries: Numpy, Pandas, OpenCV
Web Framework: Flask, PyTorch
Technology: Python 3.6+

HARDWARE REQUIREMENTS

Processor - I3/Intel Processor
RAM - 8GB (min)
Hard Disk - 128 GB
Key Board - Standard Windows Keyboard
Mouse - Two or Three-Button Mouse

MODEL ARCHITECTURE:

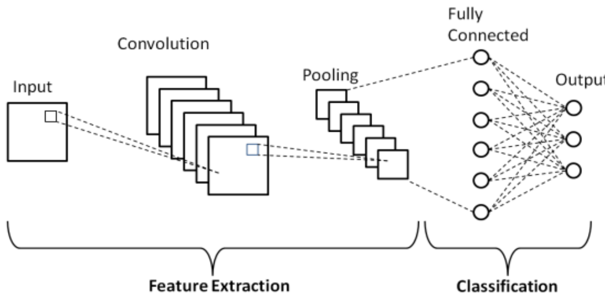


Fig.1

IV. METHODOLOGY

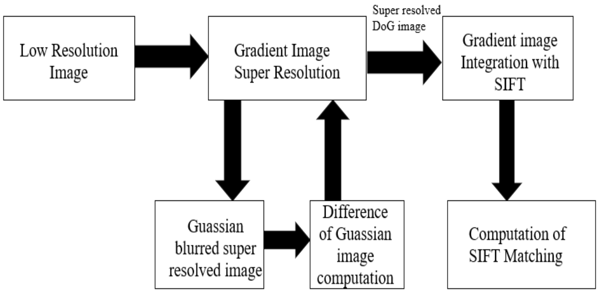


Fig.2

The SIFT technique involves generating a scale space of images with different scales and then using the Difference of Gaussian (DoG) method to identify key points in the images.
This research focuses on enhancing image resolution, particularly addressing the challenge of low-resolution images. Utilizing Gaussian blur for super-resolution and other techniques, such as generating super-resolved Difference of Gaussians (DoG) images and enhancing gradient images, aims to significantly improve image quality.

The methodology involves applying Gaussian blur for super-resolution, creating super-resolved DoG images, and enhancing gradient images. Techniques like computing the difference of Gaussian images and integrating gradient images with Scale-Invariant Feature Transform (SIFT) are employed. The computation of SIFT matching further refines image resolution, showing promising results in image enhancement.

V.RESULTS AND DISCUSSION

A comprehensive web-based model has been developed to enhance the low-resolution image to high resolution images employing a diverse array of models.

The user experience is streamlined through a user-friendly website, where the individual has to upload a low-resolution image and select the scale level as per the user requirements.

Once the image is uploaded user can start enhancing the image by clicking the enhance image button by triggering the models analysis .The results are then promptly displayed providing the before and after the enhancement adjustments.

This user friendly is dedicated to enhancing image clarity and detail, providing users with high-resolution images.

Website Homepage:

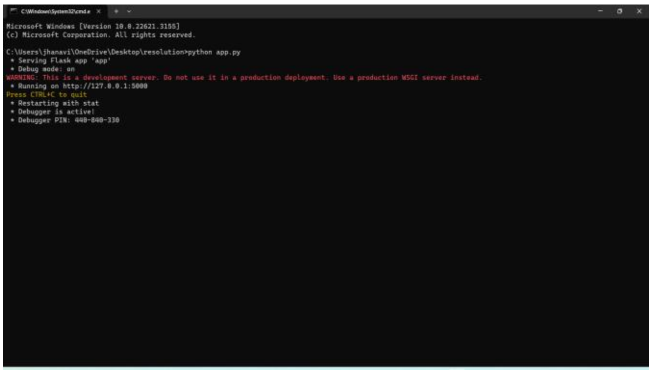


Image Upload:

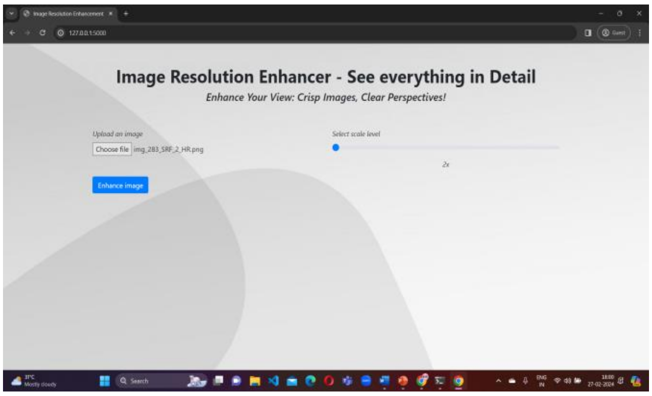
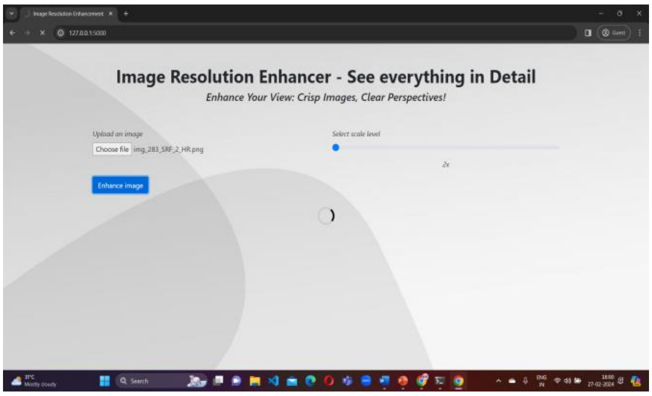
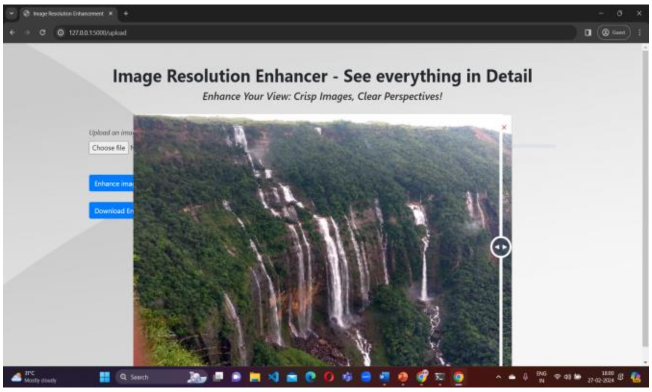


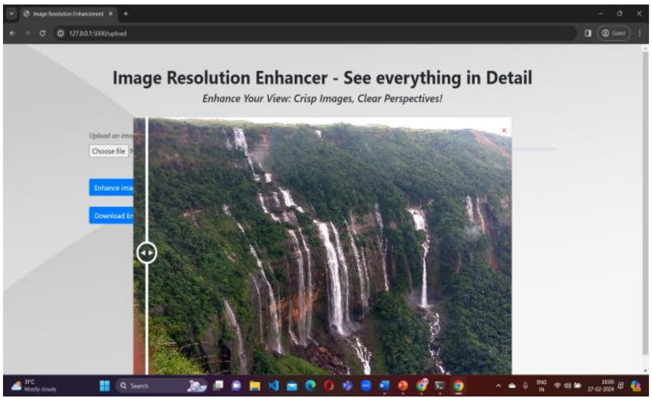
Image loading for enhancement:



Before Image Enhancement:



After Image Enhancement:



The above is the high resolution image we got. High-quality enhancements can improve clarity and detail, making images more suitable for various applications such as printing, analysis, or digital display.

VI.CONCLUSION

In summary the research highlights the role of the fuzzy pics pose sizable demanding situations for numerous scene detection troubles in real-global navigation and monitoring applications. The SR network design affords improved room adaptation in both community architecture and specification. Simulation consequences show stepped forward SR overall performance in each photo quality stages and downstream laptop vision operations together with point reconstruction in comparison to previous cutting-edge pixel-domain amazing-decision answers. In the destiny, integration of special capabilities of deep neural networks with excessive loss networks and smooth most loss networks could be finished to obtain better overall performance degrees.

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VIII. REFERENCES

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