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Implementation of an Image Enhancing Tool and Comparison of Various Single Image Super-Resolution Techniques based on Neural Networks

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Abstract- *Images that we capture today are generally high in resolution and have a lot of detail. But this changes when you digitally zoom into the picture, as it gets blurry. Also, old pictures seem to have lower resolutions due to the lack of digital camera capabilities. In this research project, our aim has been to solve this issue by using modern computing techniques. We have used Enhanced Deep Residual Networks for Single Image Super-Resolution (EDSR), Wide Activation for Efficient and Accurate Image Super-Resolution (WDSR), and Super-Resolution Using a Generative Adversarial Network (SRGAN) to successfully enhance the quality of images. Our code being written in Python, uses its various libraries to add features like a Graphical User Interface as well as a Command Line Interface (CLI) allowing the user to select the image and method of enhancement with ease. This code has been released at:https://github.com/ssameermah/Image-Enhancer.git https://github.com/NahushKulkarni/ImageEnhancer.git*

Index Terms: Image Super-resolution, Enhanced Deep Residual Networks for Single Image Super-Resolution (EDSR), Wide Activation for Efficient and Accurate Image Super-Resolution (WDSR), Super-Resolution Using a Generative Adversarial Network (SRGAN)

1. INTRODUCTION

Enhancement of digitally zoomed or old low-resolution images has been a concern for decades. Several researches have taken place to solve this issue with varied degrees of success. With significant advances in neural networks and growth in computational power, methods like EDSR, WDSR, and SRGAN have emerged. These techniques differing in base or extended methodologies, allow us to enhance any image of our choice. Generations of Image Super-Resolution are:

Generation 0: Interpolation
Generation 1: Super-Resolution Convolutional Neural Network (SRCNN)
Generation 2: SRResNet and Sub-pixel convolution for upsampling
Generation 3: Perceptual Loss
Generation 4: SRGAN [26]

From early days itself, the concept of interpolation has been used at a great scale. This method generally focuses on using the neighboring pixels in the low resolution to generate a new block for the high-resolution Image. Various types of interpolation techniques have been studied over the years. Some of the most popular ones are:

1. Nearest Neighbor
2. Bi-linear
3. Bi-cubic [26]

Getting to the second generation, SRCNN is a deep Convolutional Neural Network with the ability to use end-to-end mapping for Super-Resolution [27].

With SRCNN getting popular, emerged the idea of CNNs with skip connections. Also, known as ResNet. These are better than regular CNNs. SRResNets use residual blocks while replacing simple convolutional blocks. This makes them more accurate when compared to SRCNN [26].

Traditional methods such as MSE or RMSE, used pixel by pixel comparison that did not help in the quality analysis of enhanced images. Here arrived the method of Perceptual Loss. Perceptual loss is calculated by comparing two images from a pre-trained CNN model based on high-level representations [26].

Fourth Generation of Super-Resolution, SRGAN shows a great advantage over its prior generations and hence, it has been described in further sections.

These advancements in the field of Image Super-Resolution have helped us in using EDSR, WDSR, and SRGAN in our research project. We have used python for the implementation and have also added an option to use the program with a Graphical User Interface (GUI) or from Command Line Interface (CLI). Making it easy to use with other programs just by calling it through the command-line. Further sections describe these methods while also comparing their results based on our findings.

2. RELATED WORK

Super-resolution has been researched for a long time now, the most rudimentary approaches for Image Enhancing by Super-resolution were based on Interpolation techniques dependent on sampling theory. Lei Zhang et.al [1] proposed a non-linear, edge-guided technique of interpolating via directional and data fusion. Two observation sets in two orthogonal directions are specified for an interpolation pixel and an approximation of a pixel value is generated for each set. Another edge-guided interpolation approach is proposed by Xin Li et.al[2] where the key idea is first to estimate coefficients of local covariation on a low-resolution picture and then to adjoin the interpolation at a higher resolution based on the geometric dualité of low-resolution covariance and high-resolution covariance. Realizing the limitation of edge-guided interpolation technique in detailed realistic texture because textured areas blurred and look coherent, resulting in an unnatural super-resolution image. To overcome this Tai Y. W et.al[3] integrated learning-based SR with the edge-guided SR to reconstruct enhanced high-resolution images. Some developments in the field of super-resolution led to mapping functions between low-resolution images and high-resolution images. H. Chang et.al[4] and M. Bevilacqua et.al[5] used neighbor embedding while J. Yang et.al[6,7] proposed sparse coding. Recently, good improvements were observed in super-resolution due to deep neural networks. Chou Dang et.al[8] proposed a deep learning method for SR. This method explicitly maps the low- and high-resolution images end-to-end. The mapping is depicted as a deep convolutional neural network (CNN), which takes as its input as a low-resolution image and output is a high-resolution image. Later, J. Kim et.al[9] introduced Residual Networks, achieving a better performing super-resolution.

3. NEURAL NETWORKS

In this research project we used three networks for image super-resolution which we will be exploring in the subsequent sections.

3.1 Enhanced Deep Residual Networks for Single Image Super-Resolution (EDSR)

Recently, in terms of the SR peak signal-to-noise ratio (PSNR), deep neural networks have improved their efficiency. However, the optimal design of such networks is limited. First, the neural network models are responsive to smaller architectural modifications in their recovery efficiency. Secondly, the super-resolution of various scale factors is treated as an independent problem by most current SR algorithms, without considering the reciprocal relationship between different SR scales. As such, these algorithms require several networks to deal with scales, which need to be trained independently. While VDSR [9] could handle multiple scales combined together, it required higher computational cost and memory which was solved by SRResNet [10], however, SRResNet was limited to high-level computer vision problems. Bee Lim et.al [11] optimized SRResNet architecture by simplifying the network. This enables the ability to use low level computer vision problems for super resolution. Their approach handles both computational problems and multi-scale training. They achieved better performance by modifying the SRResNet architecture proposed by C. Ledig[10]. For producing a better suited network batch normalization layers were removed. This not only improved the performance of the network but also approximately saved 40% of memory usage as compared to SRResNet.

The efficiency can be improved in a single-scaling model by incorporating more network parameters. This can be achieved with several layers or with filters being enhanced. Increasing the number above the threshold limit can therefore lead to instability in training, which can then be overcome with the implementation of 0.1 factor residual scales.

They present scale-specific processing modules in their multi-scale architecture to manage the super-resolution at multiple levels. The first thing to reduce the discrepancies between the input images on different scales is to locate preprocessing modules at the networks head. Each module is made up of two residual blocks of 5 x 5 kernels. By adding larger kernels for pre-processing modules, the scaling aspect can be kept shallow while the broader receiving area is protected in early networks. Ultimately scale-specific upsampling modules for a multi-scale model are located in parallel for reconstruction in a multi-scale.

Some results from the project for EDSR are displayed below.

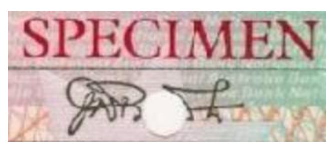
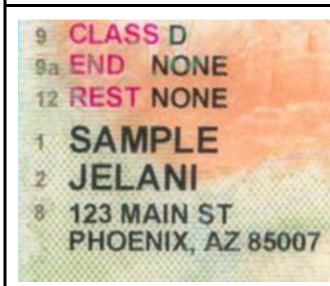
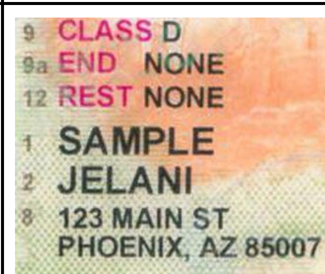
Original	Enhanced by EDSR
	
	

Table 1. EDSR Super-resolution

3.2 Wide Activation for Efficient and Accurate Image Super-Resolution (WDSR)

The process of single image super-resolution (SISR) has been successfully applied to deep convolutional neural networks (CNNs) [14, 15, 16, 17]. SISR attempts at retrieving from its low resolution (LR) version (typically a bicubic down-sampled version of HR, a high resolution (HR) picture. Past super-resolution image networks, like SRCNN[18], FSRCNN[19], ESPCN[20], used comparatively shallow convolutional neural networks (3 to 5 deep). Especially in comparison with subsequently proposed deep SR networks (e.g., VDSR[14], SRResNet[21] and EDSR[15]), they are weaker in precision.

WDSR conjectures that the variational ReLUs hinder the flow of data from shallow layers to deeper ones rather than incorporating separate workaround connections [22]. Centered on the residual SR network, it reveals that merely extending functionality before ReLU activation without additional parameters and processing leads to substantial improvements for super-resolution image, defeating SR networks with convoluted skip links and concatenations, such as SRDenseNet[23] and MemNet[24]. The premise of WDSR is that increasing functions until ReLU helps more data to flow through while also retaining deep neural networks that are extremely irregular. Thus, for improved compact pixel value estimates, low-level SR attributes from shallow layers can be simpler to transmit to the final layer.

The core concept of wide activation drives one to pursue successful ways of extending functionality before ReLU, as it is unsustainable for real-time image SR cases to merely incorporate more parameters [25]. First, WDSR-A SR residual network is added, which has a slim identity mapping path with wider (2x to 4x) channels until each residual block is enabled. SR Network WDSR-B is built for wider activation and linear low-rank convolutions. Excluding extra parameters or calculation, it has even wider activation (6x to 9x) and thereby improves precision of image super-resolution.

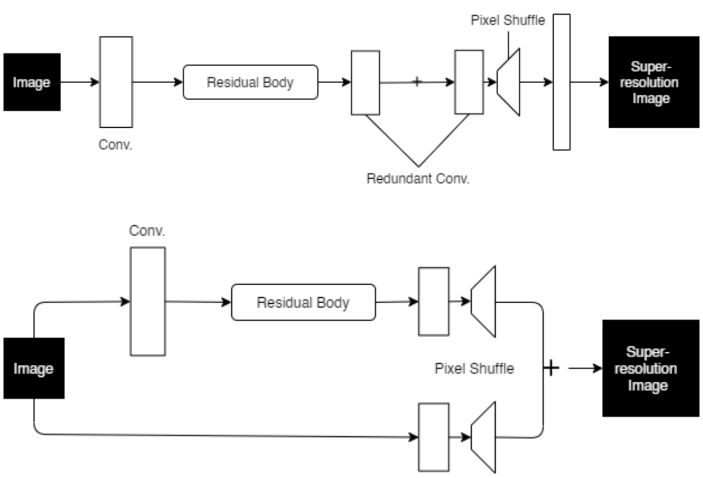


Figure 1. SR Networks of EDSR and WDSR

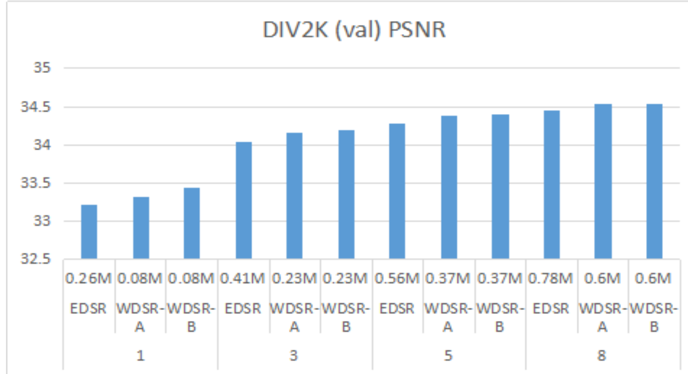


Chart 1. PSNR Comparison (EDSR vs WDSR)

Some results from the project for WDSR are displayed below.

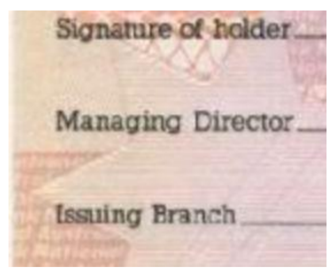
Original	Enhanced by WDSR
	
	

Table 2. WDSR Super-resolution

3.3 Super-Resolution Using a Generative Adversarial Network (SRGAN)

Recovering finer texture while super resolving at large upscaling factor was a problem. The behavior of super resolution methods based on optimization is primarily influenced by the selection of the objective function. Recent work has centered in large measure on reducing the average error of reconstruction. The consequential estimates are high signal to noise ratios, but are often unsatisfactory because they fail to meet the expected fidelity in high frequency data expected at Higher resolution. To resolve this Christian Ledig et.al[12] proposed a generative adversarial network for image super-resolution. They use a perpetual loss approach consisting of adversarial loss and content loss. This enables the network to produce super high-resolution images from heavy downgraded images. They finally proposed a super-resolution generative adversarial network by deploying ResNet with skip-connection. Skip connections relieve the network simulation architecture. However, identity mapping which is trivial to the convolutionary kernels, is potentially nontrivial. GANs provide a good basis for creating realistic and perceptually highly perceptive natural pictures. The GAN technique encourages rebuilding into the strong search area regions the chance to contain photo-realistic pictures and therefore closer to the diverse natural images.

Some results from the project for SRGAN are displayed below.

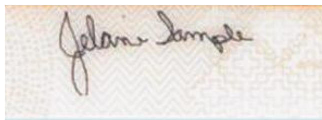
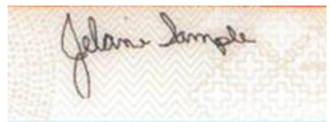
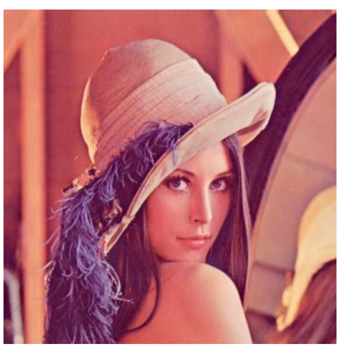
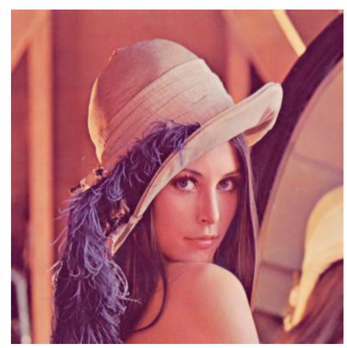
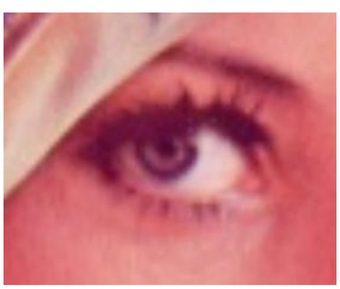
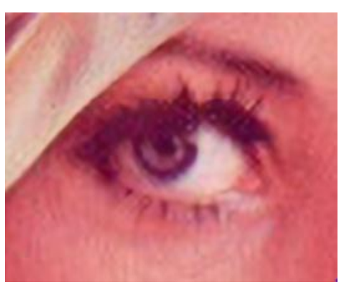
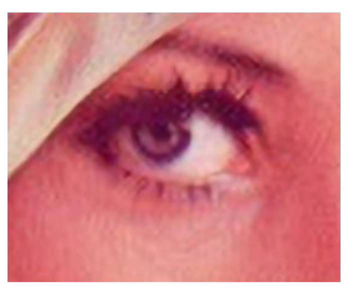
Original	Enhanced by SRGAN
	
	

Table 3. SRGAN Super-resolution

4. RESULTS

Original	EDSR	WDSR	SRGAN
			
			

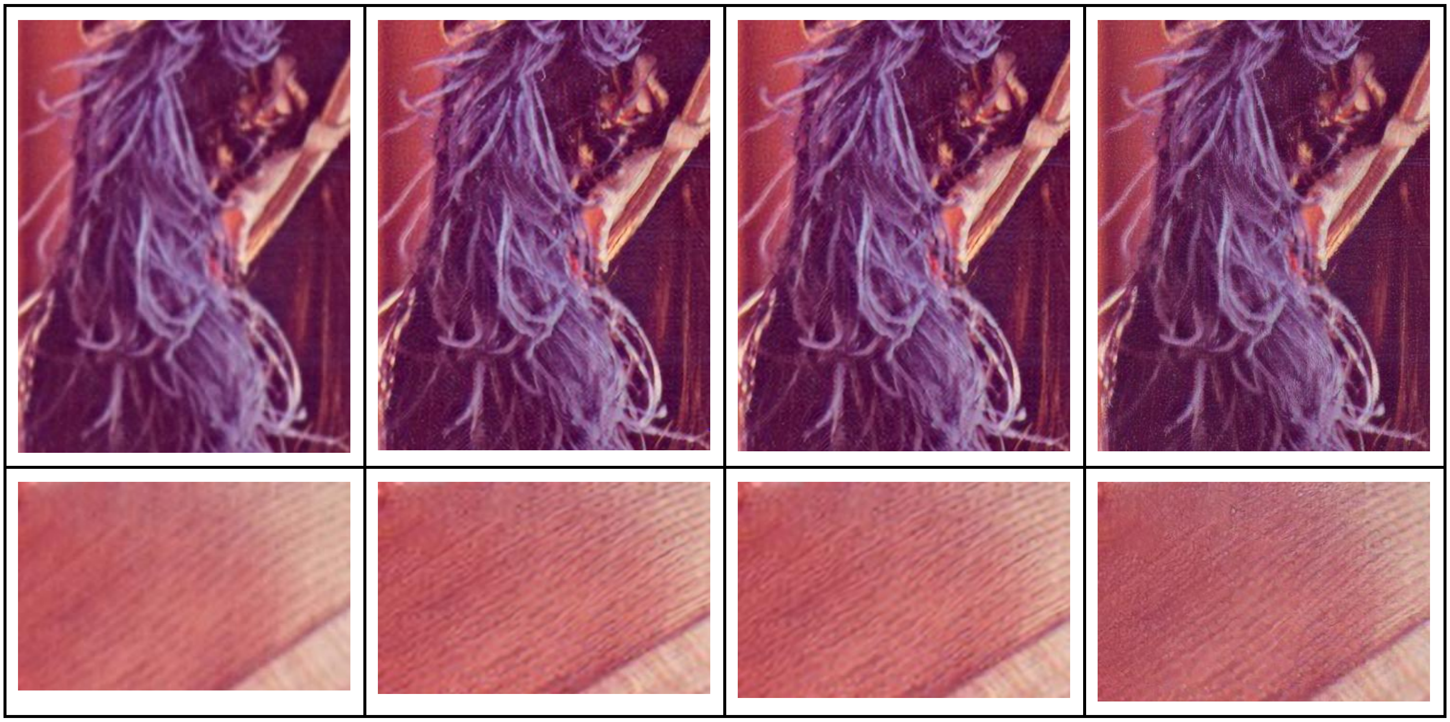


Table 4. Comparison of EDSR, WDSR, and SRGAN

5. CONCLUSION

Hereby, we can now conclude that our research project has successfully implemented a tool that uses EDSR, WDSR, and SRGAN for enhancing the quality of images while super-scaling them, also known as Super-Resolution. Our results and their comparisons establish a good sense of understanding about the scope for this field. We expect this research to help further advancements in the fields of computer vision and image processing.

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convolutional networks”. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2016, pp. 1646–1654.

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