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SPECIAL ISSUE on Medical Image Super Resolution Enhancement Using Deep Learning

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The aim of the machine learning task known as "Image Super-Resolution" is to maximize an image's resolution, usually by a factor of four or more, while preserving as much of its content and details as feasible. A high-resolution copy of the original picture is the outcome. Applications for this activity include boosting visual detail, optimizing image quality, and raising computer vision algorithm accuracy. Image Super Resolution is the process of enlargingsmall images with little drop-in quality or recovering rich information from Low Resolution (LR) photographs to create High Resolution (HR) images. Super Resolution has numerous applications like Satellite Image Analysis, Aerial Image Analysis, Medical Image Processing, Compressed Image and Video Enhancement etc.

The first paper proposed suggests an efficient sub-pixel CNN-based method called Enhanced Deep Super Resolution has been proposed, which overcomes the limitations of conventional CNN-based super-resolution techniques that are computationally expensive and require significant computational resources. Enhanced Deep Super Resolution utilizes a novel sub- pixel convolution layer to upscale low-resolution images while minimizing computational complexity. This layer rearranges feature maps in a specific order, enabling the generation of high-resolution images without introducing additional computational burden.

In the second paper, using a group of feed-forward neural networks that operate collectively, the limited recurrent neural network (LRNN) approach, a new way for improving picture resolution from multiple images is proposed. Information about previous outputs is transmitted back through recurrent connections of output units in limited recurrent networks, where it is combinedwith input nodes that flow into the network input as external input nodes. Consequently, past search expertise is leveraged, allowing LRNN to learn and search for the best solution for optimization problems in the solution space.

The third paper proposes a three-phase framework that reduces artifacts and blurring in photos while producing super resolution images while preserving low-resolution image details. Using two common techniques, the low-resolution image is enlarged to the 2x/4x scale in the first part of the process. In the second stage, a Generative Adversarial Network (GAN) powered by AI is used to improve the image.

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Enhanced Deep Super Resolution using Convolutional Neural Networks

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Abstract

Image super-resolution refers to the process of generating high-resolution images from low-resolution counterparts. Deep learning models specifically convolutional neural networks (CNNs),are widely used for this task. However, conventional CNN-based super-resolution techniques are computationally expensive and require significant computational resources. Recently, an efficient sub-pixel CNN-based method called Enhanced Deep Super Resolution has been proposed, which overcomes these limitations. Enhanced Deep Super Resolution utilizes a novel sub-pixel convolution layer to upscale low-resolution images while minimizing computational complexity. This layer rearranges feature mapsin a specific order, enabling the generation of high-resolution images without introducing additional computational burden. The proposed method has been extensively evaluated on benchmark datasets and compared to state-of-the-art approaches. This technique has significant potential in various real- world applications, including medical imaging and satellite imaging.

1. Introduction

Image super-resolution is an important task in the field of image processing, aimed at enhancing the quality and level of detail in low-resolution images. The ability to generate high-resolution images from their low-resolution counterparts has wide-ranging applications in various domains, including medical imaging, surveillance systems, and satellite imagery. In recent years, deep learning models, specifically convolutional neural networks (CNNs), have demonstrated impressive achievements in image super-resolution. However, conventional CNN-based methods often suffer from high computational complexity and require substantial computational re- sources, limiting their practicality in real-world scenarios. To address these challenges, an efficient sub-pixel CNN-based method known as Enhanced Deep Super Resolution has been proposed. This method focuses on achieving superior performance while reducing computational demands. By leveraging a novel sub-pixel convolution layer, Enhanced Deep Super Resolution reorganizes feature maps in a specific order, enabling the generation of high-resolution images without introducing additional computational complexity.

2. Working Strategy of Enhanced Deep Super Resolution Model

We have implemented a deep learning model for image super-resolution, which aims to generate high-resolution images from low-resolution ones. We utilize the DIV2K Dataset, which is a well-known dataset for single-image super- resolution tasks. The dataset comprises 1,000 images of different scenes, each exhibiting various types of degradation. To ensure appropriate data partitioning, we allocate 800images for training, 100 images for validation, and 100 images for testing purpose. For our"low quality" reference, we employ 4xdown- sampled images created using bicubic interpolation.

Dataset Preparation: The first step is to acquire or create a dataset of low-resolution images paired with their corresponding high-resolution counterparts. This dataset will be used for training and evaluating the Enhanced Deep Super Resolution model.

In the training phase, the network is trained using the prepared dataset. The low-resolution images are fed as input, and the network is optimized to generate high resolution images that closely match the ground truth high resolution images. The optimization is typically performed using loss functions such as mean squared error (MSE) or perceptual loss, which capture the difference between the generated and ground truth images.

Upscaling and Reconstruction: Once the network is trained, it can be used to upscale low-resolution images to high-resolution outputs. This is achieved by feeding the low resolution image through the network, which applies a series of operations to enhance the image details and increase its resolution. The resulting high-resolution image is then reconstructed and refined to improve its visual quality. To further improve the visual quality of the generated high-resolution images, post-processing techniques can be applied. These techniques may include denoising, edge enhancement, or artifact reduction methods [2]. To enhance the model's performance, optimization techniques such as fine-tuning or network pruning can be applied. These techniques aim to refine the network parameters or reduce its computational complexity without sacrificing performance.

Deep learning-based IQA often faces a lack of training samples. To address this, we formulate the loss function for the IQA network inspired by RankIQA [3] as follows:

$$LQA(IS\ R, IHR) = \max(0, f\ (IS\ R) - f\ (IHR) + m)$$

In equation, f(ISR) and f(IHR) represent the predicted quality scores of the SR and HR images, respectively.
A higher value indicates better image quality. The margin parameter, m, adjusts the degree of punishment for discrepancies near the boundary. To handle the insufficiency of labeled training samples, we introduce a dynamic adjustment strategy for the margin parameter, m, during training [4]. By evaluating the FR-IQA (full reference IQA) indicators that are negatively correlated with image quality, we dynamically adjust the training targets. The FR-IQA indicators' scores are unreliable, sowe utilize the moving average of these scores as the margin parameter to strike a balance between feature stability and effectiveness.

3. Result and Discussion

The experimental results demonstrate the effectiveness of the EDSR (Enhanced Deep Super- Resolution) model in the task of image super-resolution. The experimental setup involved implementing the EDSR model using Python, TensorFlow, and Keras libraries. The DIV2K dataset, known for its high-quality images, was utilized for training and evaluation. During the training phase, the EDSR model was trained on the DIV2K dataset, with careful customization of hyperparameters such as learning rate, batch size, and number of epochs. The model successfully learned to map low- resolution images to their corresponding high-resolution counterparts, capturing intricate details and enhancing image quality. Upon completion of training, the model was evaluated on the test set, and theresults were analyzed to assess the model's performance. The evaluation involved applying the trained model to super-resolve the test images and measuring quality metrics specific to image super- resolution tasks. The experimental results showcase significant improvements in image quality achieved by the EDSR model.

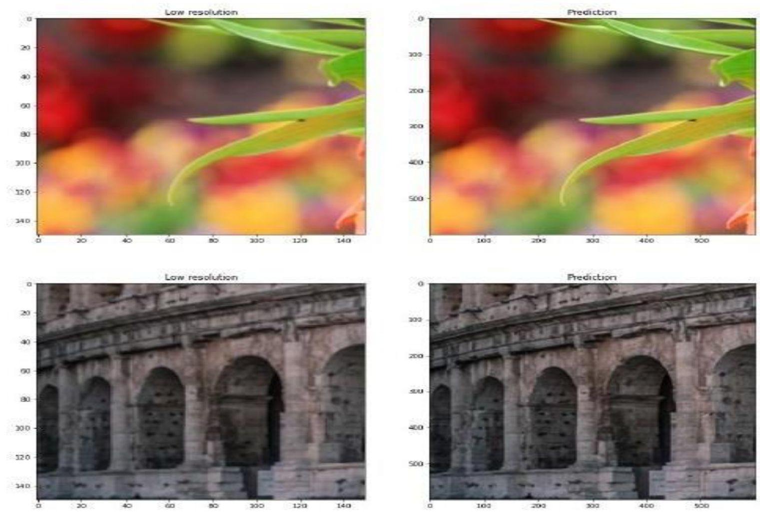

Figure 1: Image obtained after using our model

4. Conclusion

This research paper presented an in-depth investigation into image super-resolution using the EDSR (Enhanced Deep Super-Resolution) model. The research aimed to address the challenge of enhancing image resolution while preserving fine details and improving overall visual quality. The experimental results showcased the effectiveness of the EDSR model in significantly improving image quality by accurately reconstructing high-resolution images from their low-resolution counterparts. Overall, the research conducted in this paper establishes a strong foundation for image super-resolution using the EDSR model. The findings demonstrate the potential impact of deep learning-based approaches in enhancing image quality and provide valuable insights for researchers and practitioners working in the field of computer vision and image processing.

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Deep Recurrent Neural Network for Single Image Super Resolution

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Abstract

Using a group of feed-forward neural networks that operate collectively, the limited recurrent neural network (LRNN) approach, a new way for improving picture resolution from multiple images is proposed in this research. Information about previous outputs is transmitted back through recurrent connections of output units in limited recurrent networks, where it is combined with input nodes that flow into the network input as external input nodes. Consequently, past search expertise is leveraged, allowing LRNN to learn and search for the best solution for optimization problems in the solution space. Estimates produced using real video film sequences and low-resolution (LR) simulation image sequences demonstrate significant gains in both visual and quantitative aspects when compared to bilinear interpolation, as well as performance that is comparable to the frequency domain technique.

1. Introduction

High-resolution (HR) photographs are becoming more and more necessary for a variety of applications, such as military surveillance, remote sensing terrain mapping, and health diagnosis and monitoring. Using an HR image acquisition system is the most straightforward approach to improve spatial resolution, but in many commercial applications, the expensive cost of high precision optics and image sensors is always a barrier. Therefore, to get beyond these constraints of the sensors and optical manufacturing methods, a new strategy for improving spatial resolution is needed. Using image super resolution (SR) reconstruction to create an HR image (or sequence) from several observed LR images is currently one of the most promising methods [1]. Hopfield type networks are better at solving optimization issues, but they take longer to find the best answer because each relaxation reinitializes the network to its initial state, wasting the experience from the previous iteration. Similar to the RBF network, multilayered feedforward type networks are capable of dominating learning; however, they are not able to search the solution space for an optimal solution through a relaxation process. Thus, for the purpose of reconstructing SR images from multiple LR images, we present a novel limited recurrent neural network (LRNN) approach in this research.

In this study, we present a novel method for reconstructing SR images from multiple LR images using limited recurrent neural networks (LRNNs). The suggested LRNN approach can learn by varying the connection weights and relax to find the best solution in the solution space. A Gauss-Newton Real Time Recurrent Learning (RTRL) algorithm is used to train the suggested method [2]. Results of an experiment using a sequence of simulated images to show how the suggested approach, with its superior learning adaptability, can compete in solving image resolution enhancement problems.

2. Working Strategy of Enhanced Deep Super Resolution Model

We have implemented a deep learning model for image super-resolution, which aims to generate high-resolution images from low-resolution ones. We utilize the DIV2K Dataset, which is a well-known dataset for single-image super- resolution tasks [3]. The dataset comprises 1,000 images of different scenes, each exhibiting various types of degradation. To ensure appropriate data partitioning, we allocate 800images for training, 100 images for validation, and 100 images for testing purpose. For our "low quality" reference, we employ 4xdown- sampled images created using bicubic interpolation.

Dataset Preparation: The first step is to acquire or create a dataset of low-resolution images paired with their corresponding high-resolution counterparts. This dataset will be used for training and evaluating the Enhanced
Deep Super Resolution model: In the training phase, the network is trained using the prepared dataset. The low-resolution images are fed as input, and the network is optimized to generate high resolution images that closely match the ground truth high resolution images. The optimization is typically performed using loss functions such as mean squared error (MSE) or perceptual loss, which capture the difference between the generated and ground truth images.

Upscaling and Reconstruction: Once the network is trained, it can be used to upscale low-resolution images to high-resolution outputs. This is achieved by feeding the low resolution image through the network, which applies a series of operations to enhance the image details and increase its resolution. The resulting high-resolution image is then reconstructed and refined to improve its visual quality. To further improve the visual quality of the generated high-resolution images, post-processing techniques can be applied. These techniques may include denoising, edge enhancement, or artifact reduction methods [4]. To enhance the model's performance, optimization techniques such as fine-tuning or network pruning can be applied. These techniques aim to refine the network parameters or reduce its computational complexity without sacrificing performance.

Recurrent networks are employed when we can provide the network with up-to-date data, but the order in which the inputs are provided is also crucial. In order to merge the current data with the previous inputs, the neural network must maintain a record of them to generate a response. All of the neural network's processors have two-way connections thanks to fully recurrent networks. They display instability and chaotic behavior related to their power becauseof their complex and dynamical properties, and it takes them an indefinite period of time to reach a stable state.

3. Result and Discussion

The experimental results demonstrate the effectiveness of the EDSR (Enhanced Deep Super-Resolution) model in the task of image super-resolution. The experimental setup involved implementing the EDSR model using Python, TensorFlow, and Keras libraries. The DIV2K dataset, known for its high-quality images, was utilized for training and evaluation. During the training phase, the EDSR model was trained on the DIV2K dataset, with careful customization of hyperparameters such as learning rate, batch size, and number of epochs.

The model successfully learned to map low-resolution images to their corresponding high-resolution counterparts, capturing intricate details and enhancing image quality. Upon completion of training, the model was evaluated on the test set, and the results were analyzed to assess the model's performance. The evaluation involved applying the trained model to super-resolve the test images and measuring quality metrics specific to image super-resolution tasks. The experimental results showcase significant improvements in image quality achieved by the EDSR model.

Figure 1: Image obtained after using our model

4. Conclusion

We presented an improved super-resolution technique in this study. We refine the traditional ResNet design to yield better results while maintaining the compactness of our model by eliminating superfluous components. In order to train big models steadily, we also use residual scaling approaches. Our suggested singe-scale model outperforms existing models and reaches cutting edge performance. In addition, we create a multi-scale super-resolution network in order to minimize both the size of the model and the training time. With its shared main network and scale-dependent modules, our multi-scale model can handle several super- resolution scales in a cohesive manner. The multi-scale model performs similarly to the single- scale SR model, despite remaining compact when compared to a group of single-scale models. Our suggested single and multi-scale models have placed highly in the DIV2K dataset as wellas the common benchmark datasets.

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Generative Adversarial Network (GAN) for Image Super-Resolution Enhancement

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Abstract

The technique of increasing and improving a low-resolution image is known as image superresolution (SR). Industrial image enhancement, categorization, detection, pattern recognition, satellite imaging, medical diagnostics, image analytics, and other applications benefit from image superresolution. Maintaining the characteristics of the low-resolution image while enlarging and improving it is crucial. This research study proposes a three-phase framework that reduces artifacts and blurring in photos while producing superresolution images while preserving low-resolution image details. Using two common techniques, the low-resolution image is enlarged to the 2x/4x scale in the first part of the process. In the second stage, a Generative Adversarial Network (GAN) powered by AI is used to improve the image.

1. Introduction

To produce super resolution images, single low-resolution (LR) image or several LR images of the same scene might be utilized. It is still difficult to generate the super resolution from a single image, though. Since a single LR image pixel contributes to the prediction of several pixels in the super resolution image, the problem is ill-posed.

When reconstructing superresolution on larger scales, this challenge becomes more complicated; nonetheless, it can be overcome by statistically analyzing the low-level properties of image patches [1]. The super-resolution technique adds and improves thequality of pixels in a low-resolution (LR) image, which has less pixels than a high-resolution (HR) image. A low-resolution (LR) image contains fewer pixels; to equal a high-resolution (HR) image, the super-resolution approach adds and improves the pixel quality. One LR image or a series of LR photographs can be used to rebuild an image. One or more cameras can be used to capture a sequence of LR images.

In single image superresolution (SISR), an equivalent HR image is constructed from a single LR image. That is a laborious task to do. The three classes listed below, which are based on interpolation, reconstruction, and learning techniques, are primarily representative of SISR algorithms [2]. We present a framework that generates an enhanced version of the original image, called a superresolution image, from an LR image. We performed pretreatment and postprocessing on the image in addition to image enhancement. The total contributions of the research are as follows: Bicubic interpolation (BI) and A+ image enlargement methods were employed in the input image preprocessing to preserve the low-resolution image's detailed information while maintaining crisp edges and removing artifacts. We proposed the EffN-GAN architecture with an Inverted Residual Block, which can improve the overall performance of the network using a narrow-wide-narrow strategy. To obtain both low level and high level features, we constructed a dual generator GAN, one with a shallow network and another with a deep network.

2. Experimental Setup

The framework produces a superresolution image that is 224x224x3, which is equal to the ground truth. Using DIV2K pictures, patches of the same size as the ground truth and those with 112x112x3 dimensions have been made. We have used the Pro edition of Google Colaboratory (Colab) for all of our tests. We could employ GPUs or TPUs with Colab Pro, like the T4 or P100, which have high-memory virtual machine RAM of 12GB (upgradable to 26.75GB). Using the supplied MATLAB code, we preprocessed the image by enlarging it using the BI and A+ methods. Image fusion has also been coded in MATLAB for postprocessing. Additionally, EffN-GAN has trained on Google Colab with varying batch sizes; nevertheless, batch size 5 has produced superior outcomes. EffN-GAN was trained for 200 epochs with a batch size of 5, and on epoch 194, we were able to obtain a minimum discriminator loss of 0.166. 194 epochs later, the loss has begun to rise. With the datasets Set5 and Manga109, as indicated in Table 3, our suggested framework outperforms SRCNN, SRGAN, and GMGAN in terms of image quality assessment metrics. Every image in the test dataset has a higher SSIM value for 2x scaling. In addition to this PSNR value, there have been increases in the VIF from Set5, the VIF from Set14, the VIF from B100, the PSNR from Urban100, and the VIF from the Manga109 dataset [3], [4]. Table 3 illustrates how the VIF from Urban100 has been discovered less frequently than other approaches while assessing the PSNR from Set14 and B100.

Table 3: Image Quality Parameters of the proposed Super-Resolution Framework Compared to SRCNN, SRGAN, and GMGAN With 2x Scale Factors

Dataset	Image Quality Assessment Parameters	SRCNN	SRGAN	GMGAN	Proposed Framework
		2x			
Set5	PSNR	30.51	32.35	33.06	**36.67**
	SSIM	0.9014	0.9014	0.9128	**0.9219**
	VIF	0.9219	0.9219	0.9319	**0.9741**
Set14	PSNR	26.44	29.99	28.86	**30.21**
	SSIM	0.8714	0.8714	0.8811	**0.8643**
	VIF	0.8914	0.8914	0.9022	**0.9010**
B100	PSNR	25.41	27.99	28.91	**27.36**
	SSIM	0.8152	0.8211	0.8054	**0.8279**
	VIF	0.9458	0.9458	0.9351	**0.9112**
Urban100	PSNR	27.12	28.94	27.84	**25.54**
	SSIM	0.8517	0.8841	0.8854	**0.8642**
	VIF	0.8927	0.9393	0.9149	**0.9217**
Manga109	PSNR	32.91	37.84	35.98	**36.64**
	SSIM	0.9021	0.9248	0.9121	**0.9210**
	VIF	0.8721	0.9	0.9011	**0.8531**

3. Conclusion

Our approach for super resolution of a single image uses fusion as postprocessing and enlarging techniques as pretreatment. The EffN-GAN is a suggested GAN that is utilized in between these procedures. An EfficientNet pretrained model that adjusts an image's width, depth, or resolution is utilized in EffN-GAN. The DIV2K dataset served as the training dataset for EffN-GAN, and five distinct datasets—Set5, Set14, B100, Urban100, Manga109 are created. After creating superresolution images from a single image from each dataset, we have also shown the outcomes. There are three stages to the entire framework, and each stage is followed by improved image quality. Based on PSNR, SSIM, and VIF, we have compared the framework's performance with that of the well-known superresolution techniques, SRCNN, SRGAN, and GMGAN.

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