Grenze International Journal of Engineering and Technology, June Issue

A Comprehensive Review of Image Super-Resolution Methods using Deep Learning

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***Abstract*— Image super-resolution is a technique that seeks to improve the sharpness and fidelity of images with low resolutions. This process involves the reconstruction of high-resolution images from their lower-resolution equivalents, thereby enhancing the visual intricacies and overall clarity of the image. Profound comprehension of the principles governing image and video super-enhancement holds significant importance in the formulation of efficient algorithms and methodologies across diverse domains. Super-resolution is a major task in various imaging applications like medical, satellite and agriculture particularly recovering structures of interest. By considering spatial relationships, these methods aim to capture fine details present in underlying structures. Many researchers have done survey on various methods used for super resolution. The objective of this review is to offer a thorough examination of the diverse approaches employed in enhancing the resolution of images, different datasets used, and scaling factors for images used by the researchers for various applications. Finally the paper reviews the various models of Generative Adversarial Neural Networks which proves to be state of the art method for image super resolution.**

***Index Terms*— Image super resolution, Convolutional Neural Networks, Deep Learning, Generative Adversarial Neural Networks, Metrics**

I. INTRODUCTION

Image super-resolution techniques strive to boost the sharpness of low-quality visuals, consequently elevating image quality and clarity. Conventional super-resolution approaches often hinge on interpolation or reconstitution algorithms, potentially failing to grasp the intricate nuances and configurations inherent in images. [1] But with the advancement of learning based algorithms, image reconstruction has improved not only in terms of metrics but also in terms of perceptual quality. Recently deep neural networks specifically convolutional neural networks (CNNs) have made a huge revolution in various challenging tasks like super-resolution.[2] Using deep neural networks a lot of work has been done and still ongoing in the field of image as well as video super resolution. One of the main challenges is to improve the quality of image with large scaling factor. Hence deep neural networks are trained with different configurations to get the improved results. This paper tries to include state of the art methods used for image super resolution using deep learning techniques.
Figure 1 shows an example of basic architecture of deep learning neural network. The network comprises of one input layer, one output layer, and many (K) hidden layers. Depending upon the complexity of the task involved, numbers of hidden layers are used in the architecture. Various deep learning architectures are designed using

Grenze ID: 01.GIJET.10.2.176

different combinations of interconnected layers.

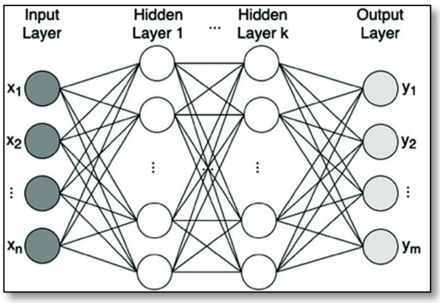

Figure 1 Deep Learning architecture example

While studying Image super resolution, few parameters need to be focused to understand the process of converting low resolution image to higher resolution image. They are resolution, scaling, interpolation, correlation and evaluation metrics. Resolution denotes the pixel count which is the number of pixels in an image. Higher the resolution better is the quality of the image. Quality can be measured in terms of certain numerical parameters or subjective parameters.[2] While improving the quality, sometimes increase or decrease in size of the image is also the requirement. This scaling can also increase or decrease the resolution up to some extent. While increasing the size of the image, the values of missing pixels are calculated by statistical parameters applied to the pixels in the neighborhood of the center pixel. This method called as interpolation, takes into consideration either one, two, four or sixteen pixels in the neighborhood for finding the values of missing pixels.[3]

Correlation describes similarity between pixel under consideration and nearby pixels. In case of spatial correlation, the relation in two dimensions is considered which is case of an image or may be a single frame of image sequence. In case of video, temporal correlation motion between the two consecutive frames needs to be considered. Temporal correlation describes relation between pixel vales of two consecutive frames. After performing image super resolution, the quality of the new image is evaluated by objective and subjective parameters called as evaluation metrics. Several standard metrics are the mean squared error (MSE), the peak signal-to-noise ratio (PSNR) and the structural similarity index (SSIM). PSNR assesses the relationship between the highest signal and noise during super-resolution. SSIM gauges the resemblance between the reconstructed high-resolution image and its low-resolution counterpart. MSE quantifies the discrepancy by computing the mean of squared differences between the pixel values of the high-resolution and reconstructed images.[1]

II.LITERATURE SURVEY

This extensive investigation seeks to investigate into the diverse methodologies employed in image enhancement for a range of practical purposes. It offers an overview of the contemporary neural network designs utilized in these strategies. Additionally, the examination encompasses the assessment criteria for performance, standard reference datasets, and the obstacles encountered in this domain. By grasping the latest cutting-edge approaches and their efficiency, scholars and professionals can acquire valuable insights into the possible uses and constraints of image enhancement for diverse applications. This understanding can subsequently steer forthcoming research avenues, promote progress in this realm, and ultimately enhance the analysis of images.

Following section describes the references in which image super resolution results are shown using Set14, Set5, BSD100 and Urban100 datasets. The recommended scales are x2 and x3. Set14 and Set 5 datasets are generally used as benchmark. Dataset BSD100 contains set of natural images in the Berkeley Segmentation Dataset. Urban100 dataset contains set of urban images.

Dong C, Loy C, He K., Tang X [1], propose the Super Resolution using Convolutional Neural Networks (SRCNN) method for performing image super resolution. They employ the T91 and ImageNet datasets for their experimental purposes. The method overcomes the traditional way to handle each component layer separately.The findings indicate that PSNR and SSIM exhibit a range between 29 and 38, and 0.78 to 0.95, respectively. Kim J, Lee J K, Lee K.M [2] use Very Deep Convolutional Networks for Super Resolution (VDSR) method for their experimentation. They use cascaded filters in 20 layers to efficiently exploit the contextual information. PSNR and SSIM vary from 27 to 37 and 0.82 to 0.95 respectively. Results compared in terms of visual improvements are noticeable.

Tai Y, Yang J, Liu X [3] suggest Deep Recursive Residual Network (DRRN) model for their experimentation. They use residual learning along with very few parameters to overcome the problem of training very deep neural networks. The system delivers PSNR values ranging from 27 to 37, along with SSIM scores between 0.8 and 0.95. Lee J K, Lee K M. [4] use Deep Recursive Convolutional Network (DRCN) for their experimentation. The model proposes a combination of three sub networks- embedding, inference and reconstruction. Addition of recursive supervision using back propagation improves the results. The system offers PSNR and SSIM values ranging from 27 to 37 and 0.79 to 0.95, respectively.

Qing Cai et al. [5] propose Texture and Detail Preserving Network (TDPN) which mainly focusses on preserving the details which improves the quality of local region. They use the DIV2K dataset for experimentation. PSNR and SSIM vary from 29 to 38 and 0.81 to 0.96 respectively along with improved perceptual quality. Ahn et al. [6] design Cascading Residual Network (CARN) for real time applications. They use the DIV2K, T91 & BSD datasets for experimentation. Experiments show that with fewer parameters cascaded networks give better results. The PSNR and SSIM metrics exhibit a range of values spanning from 28 to 37 and 0.80 to 0.95, respectively.

Li J, Fang F, Mei K, Zhang G[7] introduce the Multi-tier Residual Network (MTRN) approach for their research. They employ the DIV2K dataset as their experimental foundation. To detect significant features of various scales, mainly residual blocks are used which provide improved results. PSNR and SSIM values are in the range of 28 to 38 and 0.80 to 0.96 respectively. Lim et al. [9] suggest Enhanced Deep Neural Network for Super Resolution (EDSR) model for their experimentations. The model improves reconstruction of images of different scales into a single model. PSNR and SSIM ranges from 27 to 38 and 0.74 to 0.96 respectively.

Liu et al. [10] use Residual feature aggregation network (RFANet) for image super-resolution. The model combines more number of residual modules together to achieve better results. PSNR and SSIM achieved using this model ranges from 29 to 38 and 0.81 to 0.96 respectively. Wang et al. [11] propose Sparse Mask Super Resolution (SMSR) network for their experimentations. Using masks at local region significant features and redundant features are extracted. Ignoring redundant features quality is improved using significant features. PSNR and SSIM using the model range from 28 to 38 and 0.81 to 0.96 respectively.

Table 1 presents a comparison of PSNR/SSIM values across various scales for Set5, Set14, BSD100, and Urban100 datasets, as indicated in the aforementioned references.

TABLE I- COMPARISON OF PSNR / SSIM PARAMETERS ON SET5, SET14, BSD100, URBAN100 DATASETS FOR DIFFERENT MODELS

Model Name	**Set 5**		**Set 14**		**BSD 100**		**Urban 100**	
	PSNR	**SSIM**	**PSNR**	**SSIM**	**PSNR**	**SSIM**	**PSNR**	**SSIM**
SRCNN [1]	36.66	0.954	32.45	0.907	31.36	0.888	29.5	0.895
VDSR [2]	37.53	0.959	33.03	0.912	31.9	0.896	30.76	0.914
DRRN [3]	37.74	0.959	33.23	0.914	32.05	0.897	31.23	0.919
DRCN [4]	37.63	0.959	33.04	0.912	31.85	0.894	30.75	0.913
TDPN [5]	38.31	0.962	34.16	0.923	32.52	0.905	33.36	0.939
CARN [6]	37.76	0.959	33.52	0.917	32.09	0.898	31.92	0.926
MSRN [7]	38.08	0.961	33.74	0.917	32.23	0.901	32.22	0.933
EDSR [9]	38.11	0.96	33.92	0.92	32.32	0.901	32.93	0.935
RFANet [10]	38.26	0.962	34.16	0.922	32.41	0.903	33.33	0.939
SMSR [11]	38	0.96	33.64	0.918	32.17	0.899	32.19	0.928
SRCNN [1]	32.75	0.909	29.3	0.822	28.41	0.786	26.24	0.799
VDSR [2]	33.66	0.921	29.77	0.831	28.82	0.798	27.14	0.828
DRRN [3]	34.03	0.924	29.96	0.835	28.95	0.8	27.53	0.838
DRCN [4]	33.82	0.923	29.76	0.831	28.8	0.796	27.15	0.828
TDPN [5]	34.86	0.931	30.79	0.85	29.45	0.813	29.26	0.872
CARN [6]	34.29	0.926	30.29	0.841	29.06	0.803	28.06	0.849

MSRN [7]	34.38	0.926	30.34	0.84	29.08	0.804	28.08	0.855
EDSR [9]	34.65	0.928	30.52	0.846	27.71	0.742	29.25	0.809
RFANet [10]	34.79	0.93	30.67	0.849	29.34	0.812	29.15	0.872
SMSR [11]	34.4	0.927	30.33	0.841	29.1	0.805	28.25	0.854

Following section focusses on super resolution applied to remotely sensed images. Due to the limitations of image capturing devices or other factors like distance, the quality of images received is of low resolution. Hence super resolution plays an important role to improve quality of these images.

Lei S, Shi Z, Zou Z [12] suggest Local Global Combined Network (LGCnet) which mainly uses CNNs. Lower layers of CNN extract local features while higher layers extract global features. These layers are cascaded to get better results. They employ the UC Merced dataset for their experimental trials. The proposed approach indicates PSNR and SSIM values falling within the spectrum of 29 to 38 and 0.82 to 0.92, respectively. Ma et al. [13] propose Wavelet Transform with Recursive Res-Net (WTCRR) for to achieve super resolution. Wavelet transform is used for decomposing the image into frequency components while residual network is used to predict high frequency components. PSNR and SSIM calculated by the network ranges from 31 to 35 and 0.90 to 0.95 respectively.

Pan Z, Yuan F, Lei B [14] apply Dense Residual Generative Adversarial Network (DRGAN) to achieve super resolution. They use the NWPU-RESISC45 dataset for experimentation. Residual learning is used for generator training, which improves the performance along with the modified loss function. PSNR and SSIM vary from 31 to 35 and 0.91 to 0.96 respectively. Dong X, Xi Z, Sun X, Yang L [15] suggest Enhanced Back-projection network (EBPN) for performing image super resolution. They conducted experiments utilizing the UC Merced dataset. The suggested magnification factors are 4x and 8x. They employed a lightweight feature augmentation network technique to attain the desired level of performance. The computed PSNR and SSIM values range from 21 to 25 and from 0.58 to 0.80, respectively.

Zheyuan Wang et al. [16] recommend Feature Enhancement Network (FeNet) to enhance the resolution of remote sensing images. To improve the efficiency non-linear feature extraction is achieved by using lightweight lattice block (LLB). PSNR and SSIM achieved using the network range between 29 to 34 and 0.85 to 0.94 respectively.

Wang P, Bayram B, Sertel E [17] propose channel attention-based framework for Remote Sensing Image Super-resolution (CARS). They use the Pleiades 1a dataset for experimentation. The recommended scales are x4. Transfer learning is also used to improve the performance. The method achieves PSNR and SSIM from 30 and 0.94 respectively.

Table 2 presents the PSNR/SSIM values pertaining to remote sensing image super-resolution across various scales, methodologies, and datasets.

TABLE II- PSNR/SSIM COMPARISON FOR IMAGE SUPER-RESOLUTION IN REMOTE SENSING APPLICATION

Model	Scaling Factor	Method	PSNR	SSIM
LGC network [12]	2	CNN to extract local and global features	33.48	0.9235
	3		29.28	0.8238
WTC Recursive Res-Net [13]	2	Wavelet Transform	35.47	0.9586
	3		31.8	0.9051
Deep Residual GAN [14]	2	Residual Dense Pixel Shuffle with 2 discriminators	35.55	0.9631
	3		31.92	0.9102
Enhanced Back Projection Network [15]	4	Residual dense Back-projection network	25.48	0.8027
	8		21.63	0.5863
Feature Enhancement Network [16]	2	Light-weight Lattice Block for feature extraction	34.22	0.9337
	3		29.8	0.8481
Channel attention-based framework [17]	4	Residual Channel and Spatial Attention	30.90	0.9489

Following section focusses on the references where Manga 109 dataset and Urban 100 dataset are specifically used for super resolution. Manga 109 comprises of 109 manga volumes drawn by skilled manga artists from Japan. Urban100 dataset contains set of 100 urban images which is used as benchmark for super resolution.

Niu et al. [18] recommend Holistic Attention Network (HAN) for their experimentations. Attention modules are incorporated in CNN to achieve superior performance. The model achieves PSNR and SSIM in the range from 29 to 39 and 0.87 to 0.97 respectively. Mei et al. [19] introduce the Non-Local Sparse Attention (NLSA) approach in their experimental work. The model offers the benefits of Non-Local Attention, sparsity and hashing. PSNE and SSIM of the model vary from 29 to 39 and 0.87 to 0.97 respectively.

Lu et al. [20] propose Efficient Super-Resolution Transformer (ESRT) method for single image super resolution. The method uses lightweight model comprising of set of efficient transformers resulting in low computational losses. They use the DIV2K dataset for experimentation. PSNR and SSIM achieved by this method ranges from 26 to 33 and 0.79 to 0.94 respectively.Zhang et al. [21] use Efficient Long Attention Network (ELAN) for image SR. Using the efficiency of attention networks with shift convolution improves the results. The model states PSNR and SSIM from 28 to 39 and 0.86 to 0.97 respectively.

Table 3 displays a comparison of assessment criteria between the Manga 109 and Urban100 datasets.

TABLE III- PSNR/SSIM COMPARISON ON MANGA109, URBAN100 AND PARAMETERS OF MODEL

Model	Scale	Manga109		Urban100		Parameters
		PSNR	SSIM	PSNR	SSIM	
HAN[18]	X2	39.46	0.9785	33.35	0.9385	16.1 M
	X3	34.48	0.95	29.1	0.8705	
NLSA [19]	X2	39.59	0.9789	33.42	0.9394	16.1 M
	X3	34.57	0.9508	29.25	0.8726	
ESRT[20]	X3	33.95	0.9455	28.46	0.8574	751 K
	X4	30.75	0.91	26.39	0.7962	
ELAN [21]	X2	39.11	0.9782	32.76	0.934	8.3 M
	X3	34	0.9478	28.69	0.8624	

Following sections puts the light on use of Generative Adversarial Network (GAN) models for image super resolution. Based on various training methods for the generator and using various mappings between generator and discriminator, GAN proves to be better technique in the field of super resolution.

Christian et al. [22] use GAN for Super resolution (SRGAN) model for their experimentation. They estimate perceptual loss which is specified in terms of adversarial loss and content loss to improve the performance of the model. The recommended scale is x2 with the PSNR and SSIM values as 32 & 0.88 respectively. Along with this measures, mean opinion score (MOS) is also considered to measure perceptual quality of the model. Tero et al. [23] propose Progressive Growing of GAN model for improving the quality of image in terms of stability and variation.. They suggest CelebA dataset for experimentation. The basic principle is to grow generator and discriminator progressively to achieve better results. The recommended scale is x6 with the PSNR and SSIM values 29 & 0.83 respectively.

Guimin et al. [24] suggest unsupervised learning based GAN model for image quality improvement. They have developed a regularizer to address local –global features. They use augmented 01 image dataset for training. The recommended scale is x4 with the PSNR and SSIM values 27 & 0.74 respectively. Yong bing et al. [25] propose Multiple Cycle in Cycle GAN (MCinCGAN) models to get high resolution images. The cycles of the convolutional neural networks used depends upon the up-scaling factor of the underlying image. They use DIV2K dataset for experimentation. The recommended scale is x2 & X4 with the PSNR and SSIM score lies in the range between 25 to 27 and 0.69 to 0.74 respectively.

Table IV. PSNR/SSIM FOR DIFFERENT GAN MODELS

Model	Scale	PSNR/SSIM
SRGAN[22]	X2	32.14/0.8860
PGGAN[23]	X6	29.54/0.8301
Deep Unsupervised GAN[24]	X4	27.39/0.7412
MCinCGAN[31]	X2	26.15/0.7020
MCinCGAN[31]	X4	25.51/0.6878

Emily et al. [26] propose Laplacian Pyramid of Adversarial Network (LAPGAN) method for their experimentations. In a laplacian pyramid, convolutional networks are cascaded. Each layer of pyramid is trained using GAN to improve the performance. They employ the $CIFAR_{10}$ database for their experimentation. The suggested magnification factors are x2, and the batch size should be set to 16. They use PyTorch for experimentation. Zihan et al. [27] propose Deep Tensor GAN (TGAN) for image generation. Model uses Tensor structures for learning using GAN. They use the MNIST dataset for experimentation. The suggested scales are x2 and batch size of 32. They use TensorFlow for experimentation.
Vineeta et al. [28] perform Unsupervised Super-Resolution of Optical coherence tomography Images Using Generative Adversarial Network (USROCTGAN) to enhance the quality of OCT images. The recommended scales are x4 and batch size of 64. They use TensorFlow for experimentation. The learning rate is $2x\ 10^{-4}$. Xin Jiang et al. [29] employ the CTGAN technique in their experimental work, utilizing the LUNA dataset as their chosen experimental dataset. They propose a combination of unsupervised and supervised network for training the generator and discriminator respectively, to achieve the improved accuracy. The recommended scales are x4 and batch size of 16. The learning rate is $2x10^{-4}$. They use Tensor Flow for experimentation.
Sefi et al. [30] suggest KernelGAN method for their experimentations. Using downscaled version of low resolution images to train the generator network, it creates exact image-specific SR-kernel. KernelGAN is an unsupervised network hence does not require much training data. They conduct experiments utilizing the DIV2K dataset, with the suggested scaling factors being 2x and 4x. Their experimentation involves the application of the PyTorch framework. The learning rate is $2x\ 10^{-4}$.
Gwantae et al. [31] propose CycleGAN method for real world super resolution problems. They use unpaired dataset as against paired datasets of low-high resolution images used in various references. The recommended scales are x4 and batch size of 16. The learning rate used for the model is 10^{-4}. They use Tensor Flow for experimentation.

Table V- TYPICAL CONFIGURATIONS OF VARIOUS GANS USED FOR IMAGE SUPER-RESOLUTION

Method	Batch size	Scale	Framework	Learning rate
LAPGAN [26]	16	X2	PyTorch	0.02
TGAN[27]	32	X2	TensorFlow	0.04
USROCTGAN [28]	64	X4	TensorFlow	2×10^{-4}
CTGAN[29]	16	X4	TensorFlow	0.04
KernelGAN [30]	-	X2, X4	PyTorch	2×10^{-4}
CycleGAN [31]	16	X4	TensorFlow	0.04

This literature review offers a concise summary of the progress and techniques utilized in the field of image super resolution. The cited studies emphasize the significance of super resolution, introduce innovative deep learning frameworks, and exhibit encouraging outcomes in improving image resolution and overall quality.

III. CONCLUSION

By using the data included in the image, super-resolution stands out as a possible method for improving image quality. The major goal is to increase image resolution while preserving its quality. Understanding the spatial connections between pixels and patches within an image helps in this process. The strategy is built on learning-based techniques that use convolutional neural networks (CNNs) as a tool. These techniques are intended to convert low-resolution images into high-resolution counterparts while taking the surrounding context into consideration. This clever strategy makes sure that crucial information is preserved while improving visual quality. Convolutional neural networks, in particular, which have had a revolutionary influence on super-resolution, are at the core of this method. These networks have the capacity to understand complex mappings between low-resolution and high-resolution images on their own. This makes it possible for them to properly capture complicated structures and minute details. Within the field of image super-resolution, a wide range of CNN architectures, Generative Adversarial Networks (GANs), Residual networks, Recurrent neural networks (RNNs) and attention networks, have proven to be successful. Consequently, these architectures have significantly enhanced the visual quality of the generated images.
A combination of objective and subjective parameters is used to assess learning-based approaches to image super-resolution. Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are two objective measures

that measure the fidelity and resemblance of super-resolved images. Contrarily, subjective measurements like Mean Opinion Score (MOS) explore perceptual quality and the subjective experience of the user. The potential of learning-driven approaches within the realm of super-resolution is underscored through a comprehensive evaluation conducted by scientists. These techniques hold the capability to enhance image precision and excellence, concurrently facilitating enhanced image scrutiny and comprehension across various scenarios.

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