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Deep Learning-based Image Super-resolution Algorithms – A Survey

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Abstract: Image super-resolution (SR) is a technique of enhancing image by increasing spatial resolution of the image. By performing image SR, the pixel intensity in an image is increased. Based number of input images, the SR technique is categorized into two types as single-image SR (SISR) and multi-image SR (MISR). This work analyses different characteristics of SISR on different image datasets like medical and real-world images by using different quality factors such as peak signal to noise ratio (PSNR), structural similarity index (SSIM), and perceptual index (PI). Also, it examines the complexity of SISR schemes based on their computation time. Based on the detailed study it is identified that the deep-leaning-based SR using component learning is a best method in terms of quantitative, qualitative and computation time of generating SR image. Further, it is suggested that to improve the quality a greater number of convolutional network layers can be used in SR algorithms.

Keywords: Convolutional neural networks, spatial transform, ensemble learning, generative adversarial network (GAN), single image super resolution (SSIR)

1. Introduction

Image super-resolution is a process of converting low-resolution image (LR) into high-resolution image (HR) utilizing a single or many details from the input image [1]. SR schemes permit an image processing system to overcome to drawbacks of either LR image sensors/scanners or from any image processing phases in any application [2]. Image SR is widely used in many scientific fields such as medical image processing, remote sensing, network security, and multimedia [3]. In medical field, to examine low-resolution (LR) medical images such as computed Tomography (CT), Magnetic Resonance Imaging (MRI), Ultrasound (US) and Positron Emission Computed Tomography (PET-CT), the medical experts use SR techniques to avoid the hamper of diagnosis.

In the past decade, different kinds of SR schemes have been developed and implemented by different researchers such as interpolation-based schemes, image reconstruction-based schemes, and learning-based schemes [4]. In very latest years, the image SR have been developed by using one of the machine learning techniques called deep learning which solves many perspective problems in image processing methods and computer vision schemes such as video quality analysis, image recognition, pattern analysis, and real world image examination [5]. In SR schemes, the learning-based technique uses training of data to learn image prior. Mainly, the learning of non-linear mapping between the LR image patches and contents of high-frequency in HR is performed. Many popular leaning-based SR schemes have been suggested to optimize the quality of SR such as sparse representation using dictionary learning and anchored neighborhood. Very recently deep learning-based neural networks are widely used to develop to design optimized SR schemes [6]. Nowadays an incredibly challenging deep-leaning-based training framework composed of neural networks called generative adversarial networks is widely used to prove that the produced SR is highly realistic and very-sharp as compared with other SR training methods [7].

SISR characteristics can be improved or analyzed by using different criteria like model framework, network design and learning strategies. In past recent years, many proposals have been suggested to optimize the quality of SR by different researchers by optimizing the neural network design. This paper investigates the different SR schemes based on their technology used, neural network (NN) model, quality, and computation time. Further it mentions the merits and demerits of different SR schemes. This work analyses

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recently developed NN models such as fast conceptual deep auto encoder (FCDA) [8], larger dictionary model (LDM) [9], spatial transform to reduce geometrical effect (STRGE) [10], low-complexity convolution kernel (LCCK) [11], deep convolution with residual network (DCRN) [12], recurrent fusion network (RFN) [13] , generative adversarial network and multi-perspective discriminator (GAN & MPD) [14], component learning (CL) [15], deep and shallow network (DSN) [16], complementary priors and ensemble learning (CPEL) [17] and two discriminator network (TDN) [18]. So, the major contributions of this are: briefing different deep learning architecture recently used for image super resolution, comparing the characteristics of different architecture in terms of NN model and quality, and suggesting research scope for future developments.

The remaining portion of this paper is organized as follows. Section II describes the characteristics of different SR schemes. Section III compares the characteristics of Sr schemes and section IV provides the conclusion and future scope of the deep learning on SR techniques.

2. Different Schemes Of Deep Learning-Based SR

This section briefs different recent DL-based SR schemes and explains their architecture, and a few characteristics like PSNR, SSIM, PI and computation time.

Zeng et al. 2015 [8] proposes a SR algorithm using coupled deep auto encoder (CDA). This algorithm performs both the learning LR patches and HR patches simultaneously to reduce the computation time. It also uses big-data function to map the representation of LR corresponding to the HR. Auto encoder is an unsupervised learning which reduces the error in the reconstruction process. CDA uses three phases of operation to improve the resolution of images such as learning HR and LR patches, transforming LR into HR, and producing SR. CDA uses three-layers of forward process network and it uses back-propagation to fine tune the HR image by using the output of non-linear mapping function. It uses 36 layers for the up-scaling factor of 2. This SR algorithm is implemented by using MATLAB. The highest PSNR is 40.44 dB for the scaling factor 2 on Set5 images with the computation time of 0.43 seconds. By comparing with other related SR schemes, the CAD-based SR outperforms in both producing quality and computation time. The computation time of other SR methods such as beta process learning-based SR (BJDLSR)[19], SR based on non-negative neighbor embedding (NNESR) [20], SR through neighbor embedding (NBSR)[21] , SR based on anchored neighborhood regression [22], and SR using deep convolution (SRDC) [23] is 372.80, 17.59, 6.16, 0.78 and 2.95 seconds respectively.

Zhao et al. 2017 [9] developed a SR algorithm using dictionary model and the features of DL (DMDL). This SR scheme performs operation on three different steps such as extracting the features of HR and LR training images by using DL network, generating sparse representation to train the dictionary, and producing SR from LR image. The sub-space DL network of this SR model is termed as KernelPCANet which is used to train image feature. The KernelPCANet is a combination of CNN and principal component analysis (PCA) which is used to attain high-informative content from training dataset. This SR model is simulated by using MATLAB R2015b and Ubuntu 14.04 OS as well as by using different datasets like BSD500, Set14, and Set37. This method achieves higher PSNR as 39.46 dB and SSIM as 0.9218 with the computation time of 42.594 seconds. The other competitive SR algorithm called SR using sparse representation (SRSR) [24] produces low PSNR and SSIM as compared with [9] with high computation time. The PSNR of [24] is 33.65 dB SSIM is 0.8745 and computation time is 2.256 seconds.

Jiang et al. 2019 [10] proposed a very deep spatial transform (VDST) for image super-resolution (SR) to reduce quality loss of image while doing geometry transformation and to reduce distortion. This spatial transform (ST)-based SR consists of two modules, the first module is used to estimate the geometry transformation and the second module is used to produce HR image. A loss function which is used here is utilized to reduce the transformation errors and to decrease the errors the in the process of LR into HR. Further, this scheme improves the learning and it reduces the content corruption. This SR scheme utilizes 20 layers in the convolutional networks. This SR algorithm is a combination of both very deep convolutional networks-based system (VDSR) and ST. This VDST achieves a highest PSNR as 27.11 dB for the scaling factor 2. But the related method [25] achieves less PSNR as 25.29 dB, respectively. The SSIM for this scheme is 0.8623 for the scaling factor of 2. But STN [25] achieves a little bit high SSIM as 0.8629.

Shang et al. 2019 [11] developed a fast SR algorithm for diagnosing medical images like retina using three convolutional layers. This SR algorithm uses sub-pixel layer with single up-scaling filter to covert the LR image into HR image with less time of computation. The sub-pixel layer performs periodic shuffling to reconstruct the LR image. To reduce the time of computation, it also uses 3 * 3 kernel instead of 5 * 5 high accuracy complexity kernel. All three convolution layers use Gaussian distribution and it uses Euclidean operator. This algorithm is implemented by using Windows 7 and MATLABR2016 with CUDA v8.0 and Anaconda2 toolkits. For experimentation, it uses dataset of Berkeley segmentation ant it uses 128 and 32 datasets for training and testing, respectively. The high-speed SR produces highest PSNR as 38.90 with 0.293 seconds. But the related SR schemes such as SR with sparse prior (SRSP) [26], SR with deep convolution (SRDC) [27] and SR with efficient sub-pixel (SRES) [28] provide less PSNR as 37.90 dB, 37.84 dB and 37.95 dB respectively as well as high SR time as 4.957 seconds, 2.460 seconds, and 0.346 seconds respectively. This SR technique mainly used for studying diabetic retinopathy and it can also be used for retina segmentation.

Liu et al. 2019 proposed a SR using deep convolution network (SRDCN) which consists of parametric-rectified linear units, skip connection of identity, and convolutional layers [12]. It combines the differences between LR and the restricted image for getting final SR image. This algorithm uses highly optimized loss function which includes three units such as mean squared fault loss, feature loss, and style loss. The architecture of this SR model consists of five convolutional layers and three sub-pixel layer with the 3 * 3 kernel. For experimentation, this SR algorithm uses images from the database of ImageNet as training dataset and for testing it uses several datasets like DIV2K, Urban100, BSD100, Set14 and Set5. This SR method is simulated by using Tensorflow and provides a higher PSNR and SSIM as 37.94 dB and 0.9593 respectively for the scaling factor of 2 on 24 x 24 image dataset if Set5.But the related other SR method that is SR with recursive convolutional network [29] achieves PSNR as 37.63 as well as SSIM as 0.9588.

Yang et al. 2019 [13] proposed a SR using deep recurrent fusion network (DFRN) with large factors by utilizing transposed convolution for up-scaling and recurrent residual network for final SR. The other important function of this SR model is feature extraction unit with three layers of convolution for extracting jointly the raw features. Further a parametric-rectified linear activation operator is also involved to optimize the SR process. The recurrent residual unit recovers high-frequency content from the HR image and the recurrent three-level fusion network is used to reconstruct HR image. To analyze the quality of this SR model which uses Berkeley dataset for training and different test dataset like Set5, Set14, BSDS100, ImageNet400, and Urban100. This SR schemes achieves higher PSNR and SSIM as 37.71 dB and 0.9595 respectively with the information fidelity criterion (IFC) of 8.927 for the scaling factor of 2 on Set5 dataset. The other related SR scheme such as A+ [30] and jointly optimized regressors [31] provide only low PSNR, SSIM and IFC as compared with this SR [13].

Lee et al. 2019 [14] provided a SR scheme by using GAN and multi-perspective discriminator (GANMPD) to separate the artifacts of checkerboard on high-frequency domain and to pleasing high-frequency contents, respectively. The GAN consists of a single generator network and three discriminator networks. The generator utilizes several convolutional layers, 16 residual units and single sub-pixel layer. The discriminator utilizes eight convolutional layers with 3 x 3 kernels, two layers of dense and sigmoid operator. Discrete Cosine Transform (DCT) is used in the discriminator to decrease the checkerboard affects. This SR scheme is evaluated by using several datasets such as DIV2k, set5 and Set14. It provides a highest PSNR as 30.66 dB and SSIM as 0.9175 with PI value of 3.5986. The other related methods such as GAN-based SR using perceptual content losses (GANPCL) [32] and GAN with dense skip connections (GANDSC) [33] provide PSNR, SSIM and PI as 29.13 dB, and 3.9669 and 29.13, 0.9120 and 3.9669 respectively.

A fast image SR with component learning (SRCL) is developed by [15]. This SR involves different steps such as converting LR into HR, optimizing HR image by using CNN, and residual leaning to optimize both high- and low-frequency contents by using global decomposition. Therefore, it includes three major modules like decomposition unit and representation module, feature extraction with mapping module and a combination module. The feature extraction unit with mapping utilizes several convolution layers. To evaluate the quality of this SR scheme, various datasets have been used such as Berkely segmentation, Set5 and B200 datasets. This SR scheme achieves a highest PSNR as 37.65 and SSIM as 0.9599 with the computation time of 0.053 seconds for the scaling factor of 2 on Set5 datasets. The other related methods like deep convolutional neural network (DnCNN) [34] and deep residual learning network (DRLN) [35] provide a little bit less PSNR and SSIM, however these methods perform operations with high speed as compared with SRCL [15]. The computation timer of DnCNN [34] and DRLN [35] is 0.43 and 0.33, respectively. Another existing low-complexity SR scheme is SR with deep convolution network which operates with 0.12 seconds for generating PSNR as 37.53 and SSIM as 0.9587 [36]. Wang et al. 2019 [16] implemented a SR using deep and shallow convolution networks (SRDSCN) which consists of feature extraction, up-scaling, and multi-scale reconstruction units. The feature extraction unit includes three convolutional layers with 3 x 3 kernel and interleaved by using rectified-linear unit and this arrangement acts as non-linear mappings. The up-scaling is performed by un-pooling operation and operation and deconvolution. The up-scaling unit consists of two convolution layers with 1 x 1 kernels. The reconstruction unit consists of residual modules. To perform mapping operations, it uses a 1 x 1 kernel convolution and it also consists of other four convolution layers with the kernel of 1 x 1 size, 3 x 3 size, 5 x 5 size, and 7 x 7 size. Another important module of this SR scheme is that a shallow network which also take the LR input and produces HR image by using three trainable convolution layers with 3 x 3 kernel and produces feature map. The final HR image is upscaled by 5 X 5 convolution. Different datasets like Set5, Set14 and BSD100 are used for both training and testing. This SR scheme is trained by three deconvolution layers with 14 x 14 size, 15 x 15 size and 16 x 16 size respectively for the different up-scaling factors 2, 3 and 4. This SR scheme provides higher PSNR as 37.78 dB and SSIM as 0.9609 for the scaling factor of 2 on Set5 dataset. The other related SR methods like deep networks for SR (DNSR) [37] provides PSNR as 36.93 and SSIM as 0.9552 as well as ensemble-based deep network for SR (EDNSR) [38] provides PSNR as 37.53 and SSIM as 0.9587.

Lyu et al. 2020 [17] implemented a super-resolution algorithm using complementary priors and ensemble learning (SRCPEL) for MRI research. The structure of this SR model involves different process such as down-sampling original image to obtain LR image, enlarging LR image as well as obtaining five different types of datasets by using five different algorithms like bi-cubic interpolation, sparse coding, edge-directed interpolation, neighborhood regression and zero-interpolation filling, generating adversarial networks, ensemble learning and producing final SR image. For generating adversarial networks, this method uses gradient penalty and Wasserstein distance. The GAN is also equipped with discriminator and generator block. The generator block consists of 7 convolution layers, layer normalization unit, and an activation operator. The discriminator also consists of five convolution unit, layer normalization unit, an activation operator, and a layer of average pooling. This SR scheme is developed by using Tensorflow and it uses single coil dataset. This method achieves higher PSNR as 36.06 dB and SSIM as 0.920. But the related SR methods such as accurate SR using CNN (ASRCNN) [39], fast and accurate SR using Laplacian network (FASRLN) [40] provide PSNR as 28.87 dB and 28.80 dB respectively as well as SSIM as 0.873 and 0.884, respectively.

Choi et al. 2020 [18] suggested a SR using deep learning (DL) (SRDL) to improve the quality of up-scaled images by using a discriminator and two predictor networks. This SR model consists of up-scaling unit, feature extraction units both of shared and scale-aware. The discriminator consists of several layers of convolution and sigmoid activation operator. This SR model is verified by using different datasets like Set 5, Set 14 and BSD100 and which provides higher PSNR as 31.36 dB and SSIM as 0.870 on dataset5. Further it also proves that the perceptual quality of the SR image by measuring perceptual index (PI). The PI of this method on dataset Set5 is 4.238 which shows that this SR model makes balance between qualitative quality and quantitative information of the SR image. But another related SR called enhanced up-scaling for SR (EUSR) [41] has higher PI value 5.949. The high-PI value shows that poor quality of perceptual.

3. Comparative Analysis

This section compares the different characteristics like PSNR, SSIM, computation time and PI values of different recently developed deep-learning-based image super-resolution (SR) algorithms.

Table I describes the characteristics of different SR methods based on their technology, number of layers used in neural networks, PSNR and SSIM. . Based on Table I, it is noticed that the auto encoder-based DLSR [8] provides higher PSNR with 36 convolutional layers and as illustrated in Section III the computation time of this SR algorithm is 0.43 seconds. The second high PSNR value is generated by dictionary model-based SR which provides 39.46 dB PSNR by using several convolutional layers. However, the complexity of these SR schemes is little bit high with as compared with other SR schemes as [S9] uses 36 convolutional layers and it takes more time as compared with other techniques like [S30] component learning-based SR which achieves 37.65 dB PSNR and 0.9599 SSIM with the computation time of 0.053 seconds. So, based on the computation time and SSIM, this can be considered as fast and high-quality SR-scheme using deep learning. Further, it is understood that by using a greater number of convolutional layers, the quality of the SR can be improved and at the same time it takes more time to generate SR image. Furthermore, as Section II summarized, only [18] and [14] have identified the PI values. The PI value of [18] and[14] is 4.238 and 3.5986, respectively. Based on PI value and SSIM, it can be concluded that the GAN-based SR algorithm has more perspective than [18]. However, the PSNR is exceptionally low as compared with many of the SR algorithms listed out in Table I. Figure 1 illustrates the quality of different deep leaning-based SR algorithms in terms of PSNR. Figure 2 illustrates the SSIM characteristics of various SR algorithms. Only a very few SR methods analyze the computation time to prove the computational complexity of the specified algorithms. Figure3 provides the comparison of PSNR and computation time of different SR algorithms like [8], [14], and [30].

Based on Figure 1, almost all recent developments based on deep leaning convolutional network-based SR algorithms generates good SR as all PSNR values on above 30 dB except VDST [16]. Based on Figure 2, it is identified that VDAST [16], SRDCN [22], SRCL [31], and SRDSCN [34] perform SR with higher perceived quality of SR by generating high-valy SSIM.

As shown in Figure 3, auto encoder-based SR method (CAD) [8] operates with high quality as well as less computation time. Usually the complexity of SR generation deepens on number of convolutional layers in the deep learning algorithms. SR method [8] uses only convolutional 36 layers, so it produces high PSNR with less computation time. But another method called dictionary model-based SR (DMDL) [14] also produces high PSNR but it requires more computation time. Again, recently SRCL [30] reduces computation time by maintain the quality of SR image.

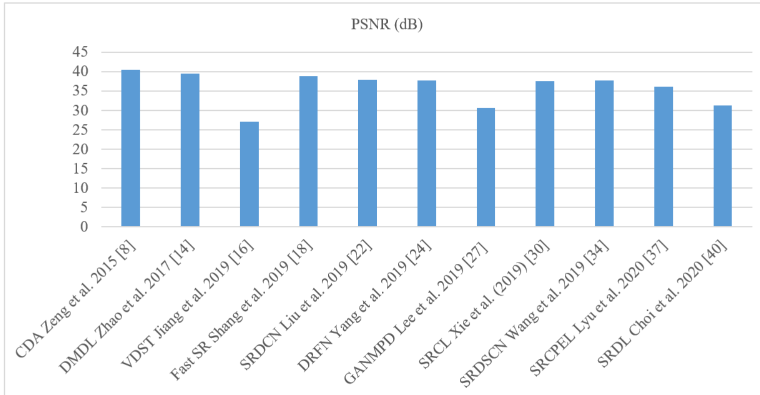

Figure 1. PSNR (dB) value of different deep learning-based SR algorithms

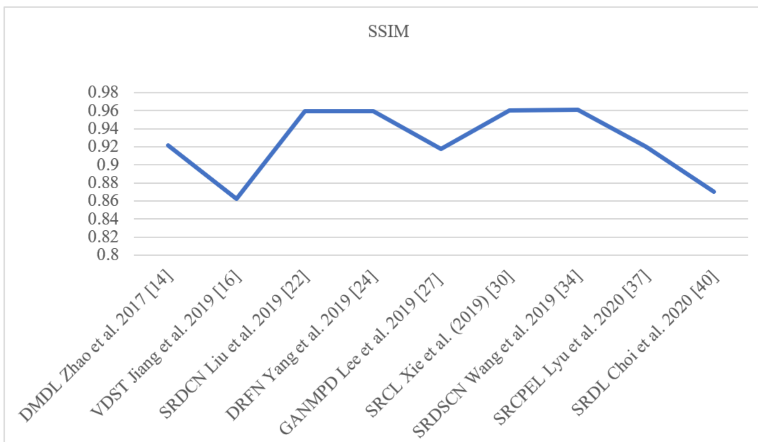

Figure 2. SSIM characteristics of various recent deep learning-based SR algorithms

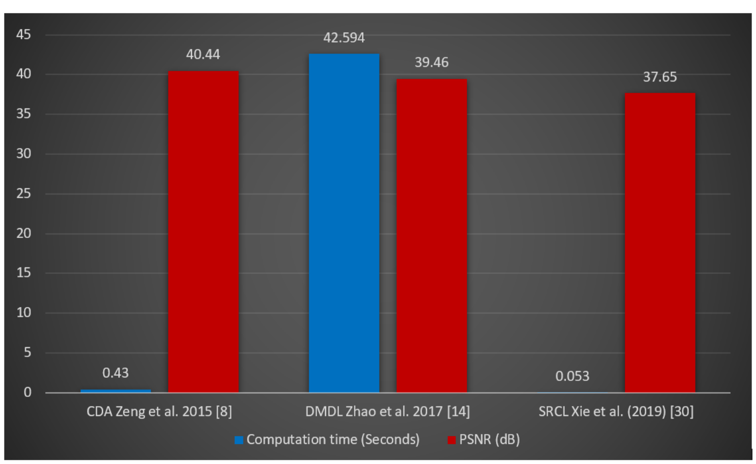

Figure 3. Comparison of PSNR and Computation time of recent deep learning-based SR methods

TABLE I. COMPARISON OF PSNR AND SSIM OF DIFFERENT SR SCHEMES

SR Scheme	NN model	No. of layers	PSNR (dB)	SSIM	Usage/ Images/ dataset	Merits	Demerits
CDA [8]	FCDA	36	40.44	NA	Set5 dataset	Reduces the reconstruction fault; Fastest algorithm	Additional pre-processing and fine-tuning steps required; No reliability confirmation
DMDL [14]	LDM	Several	39.46	0.9218	Real world images	Strong anti-interference of noise; Higher feature concentration	Required larger dictionary model; Large-computation time
VDST [16]	STRGE	20	27.11	0.8623	Real world images	Suitable for different kinds of datasets; Reduces the effects raised by geometric transformation	Required to extract deeper features; Required multiple networks to handle different kinds of transformations.
Fast SR [18]	LCCK	3	38.90	NA	Retinal segmentation & diabetic retinopathy	Simple;Higher-potential	Less receptive field; Required additional convolution layers
SRDCN [22]	DCRN	8	37.94	0.9593	Real world images	Produces accurate edge information and provides fine texture; Low-computational complexity	Missing of specialized rules and network strategies;Low-speed
DRFN [24]	RFN	9	37.71	0.9595	Deblurring and Denoising on Real world images	Larger field of receptive;Suitable for images with large scale	Increases computation time by increasing the depth of recurrent block; Required larger storage space
GANMPD [27]	GAN&MPD	Several	30.66	0.9175	Set5,Set14,DIV2k	Suitable to retrieve high-frequency components; Lowest-perceptual index	Additional discriminators are required;Low similarity due to adversarial loss
SRCL [30]	CL	Several	37.65	0.9599	Berkely segmentation, Set5 and B200 datasets	Utilizes a smaller number of parameters; Fast	High-computation complexity; Additional up-sampling filters are required
SRDSCN [34]	DSN	16	37.78	0.9609	Set5, Set14 and BSD100	Higher-accuracy in producing high-frequency information; Simple architecture	Slow; Extra training of network is required
SRCPEL [37]	CPEL	13	36.06	0.920	Medical (MRI)	Reduces effects of artifacts; Utilizes less number of parameters in network training	More computation resources are required; Not giving phase information
SRDL [40]	TDN	Several	31.36	0.870	Real world images	Suitable for different up scaling scenarios; Balance between perceptual and quantitative quality	Large computation time; Additional predictor network is required

4. Conclusion

This work studied the structure and characteristics like peak signal to nose ratio, structural similarity index measure, computation complexity, and perspective index of several recently developed deep learning-based super-resolution algorithms for single image super-resolution. Based on the detailed study, it is concluded that both auto encoder-based super-resolution algorithm and dictionary model -based super-resolution algorithms are better in generating high-quality SR image. In recent years, several low complexity super-resolution techniques have also been suggested to reduce the computation time. One of the low complexity methods is that convolution kernel-based super-resolution algorithms which uses only three convolutional layers to reduce the complexity of SR creation. Based on the computation time, it is concluded that component learning-based SR scheme is fast in operation and it also generates a good PSNR to prove the quality of SR too. Very few methods only proved the perspective characteristics of the SR algorithms by measuring perspective index value. Based on perspective index, it can be concluded that generative adversarial networks-based algorithm is more perspective than other SR algorithms. Based on structural similarity index measure it is concluded that deep and shallow networks-based super-resolution algorithm is best in giving originality in SR as it gives highest SSIM as 0.9609 as well as it also gives a good PSNR as 37.78 dB with 16 convolution layers. Based on overall observation, it is suggested that by increasing convolutional layers, the quality is increased and by reducing ad using moderate number of convolutional layers both quality and computational complexity can be maintained to generate good SR image by fast. So, further researches can be carried out to maintain the quality of SR by using a smaller number of convolutional layers as well as to improve the quality of SR by using moderate number of convolutional layers. Therefore, it is concluded that based on the purpose or applications researchers can select the SR algorithms for further development.

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