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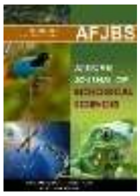

Empirical Evaluation of Convolutional Neural Networks for Denoising Images

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Abstract

Noise removal from images, or image denoising, is a critical task in computer vision, aiming to enhance image quality by suppressing unwanted random variations while preserving essential features. Convolutional Neural Networks (CNNs) have emerged as a powerful tool for this purpose, leveraging their ability to learn hierarchical representations of data. This survey provides a comparative analysis of various CNN-based techniques used for noise removal, focusing on their architectures, performance, and unique contributions. The effectiveness of denoising techniques is typically evaluated using metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). Higher PSNR and SSIM values indicate better denoising performance. CNN-based methods, particularly those with deeper architectures, generally achieve higher PSNR and SSIM scores compared to traditional methods like Gaussian filtering or wavelet-based denoising. CNN-based techniques for noise removal have demonstrated significant advancements in both performance and versatility. Traditional deep CNNs, autoencoder-based approaches, GANs, and RNNs each offer unique strengths and trade-offs. Future research is likely to focus on improving computational efficiency, robustness to diverse noise types, and the ability to generalize across different domains, thereby broadening the applicability of CNN-based denoising methods in real-world scenarios.

Keywords: Image Denoising, Convolutional Neural Networks (CNNs), Residual Learning, Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM).

1. Introduction and Literature Review

Image Denoising is a process of extracting signal x from y by removing the noise n. **y=x+n.** Convolutional neural Networks (CNNs) are being used for the extraction of features from the images and classifying the images into a single class according to their features. While working on the problem for different operations on images, the images that are being taken under consideration are the best quality images but mostly in real life, the images which are being acquired have different types of noise degradations. For example, hazy weather due to the presence of fog, charged particles, and images taken by low-resolution cameras will provide us the blurry images. Images taken by fish-eye cameras will provide distortions in the spatial coordinates. Images taken by security and surveillance cameras, and medical imaging facilities, may produce low-resolution images due to the storage capacity. Salt and pepper noise is added to the images due to electrical charges. White Gaussian noise is present in all images since it adds thermal chip noise and approximates the Poisson shot noise. These problems have been studied by constructing datasets of various kinds of degraded images and by adding various types of noise There is also an absence of a single algorithm that will work for all types of degradations. The different types of noises that are taken under consideration are hazy images, salt and pepper, gaussian blur, low-resolution images, and underwater.

The CNN-based models are made to work on these images to remove the noise from the images. The CNN uses supervised learning in which they work on a set of images during training and they work on test cases to remove the noise from the image

To remove haze from hazy images, many models and algorithms were developed to get a haze-free clear image. Early methods for haze removal were developed on extracting features of clear images such as the dark channel prior method, color attenuation method, and non-local method. The haze removal algorithms work on the differences between the intensities of pixels which does not reflect the similarity between the restored image and the underlying clear image. To address this issue, Li et al. [1] proposed a single image dehazing method using a conditional generative adversarial network (GAN) with L1 loss, adversarial loss, and perceptual loss. Zhou et al. [2] proposed a CNN network for dehazing by having GAN on perceptual loss by going by pix2pix. Liu et al. [3] proposed a method for detecting regions of blur in images and the types of blur in these regions.

For the research on low-resolution images, Wang et al. [4] started working on the classification of images with low resolution. To get the high-resolution image from a low-resolution image, single image super-resolution (SISR) [5] is the method that is generally used for increasing resolution. Dong et al. [5] first proposed a method for mapping between low and high resolution images for SISR. Tai et al. [6] developed a SISR model having 52 convolutional layers. Zhang et al. [7] proposed a novel method to have SISR by having a dense network of residues. Hui et al. [8] proposed a fast and accurate SISR via an information network.

For the research on salt-and-pepper images, Dinga et al. [9] proposed a model by providing weights to good pixels and less weights to salt-and-pepper pixels. Fu et al. [10] proposed a denoising method using patches. Later Fu et al. [11] developed GAN for salt-and-pepper denoising

As the research conducted on Gaussian-blurred images, Flusser et al. [12] introduced a new theory of invariants to model and remove Gaussian blur. Many deblurring methods have been developed for removing Gaussian blur. Alamri et al. [13] proposed to use four types of image-deblurring techniques based on the Wiener filter, Regularized filter, Lucy Richardson deconvolution algorithm, and Blind deconvolution algorithm, respectively, to handle Gaussian blurs. Tang[14] proposed a method for focusing on defocus blur areas by convolutional neural networks.

In this literature, methodologies are followed to denoise images of different sizes using convolutional neural networks. PSNR (Peak Signal to Noise Ratio) of low-resolution images has been increased whereas the brightness has been modified in the case of salt and pepper and hazy images.

The following sections explain the various methods for denoising the images using Convolutional Neural Networks

2. Methodologies, Results, and Discussion

2.1 Low-Resolution Images A large amount of degradation is visible due to capturing images of low-resolution by security cameras. To remove the blur due to low resolution, the SISR (Single Image Super Resolution) method is used. The low resolution can be represented mathematically as

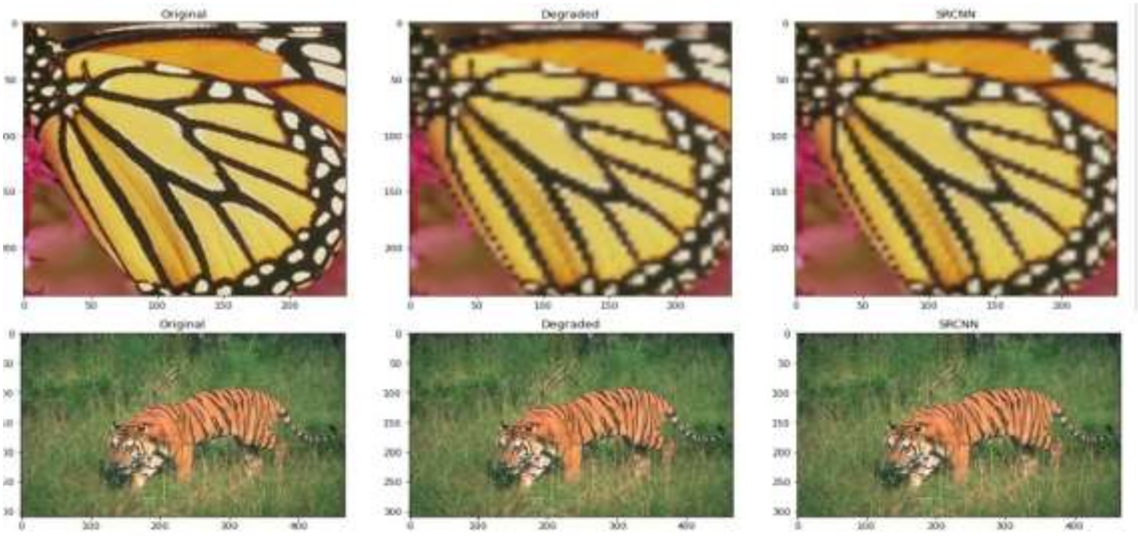
$$y = (x \otimes \mathbf{k})\downarrow_s + n \quad (1)$$

where y is the noise-free pixel value which is derived from the convolution between unknown pixel x and kernel k with down scaling by factor s and n is the independent noise present. While using the CNN, to remove the blurriness during training, the high-resolution images of training datasets are being compressed to smaller sizes like (60,60) or half of w*h dimension to w/2*h/2 dimension. Then they are rescaled back to their original size by using the bicubic interpolation method. An amount of data gets lost due to scaling and rescaling of images.

After rescaling, the images are passed through the Convolutional Neural Networks having 3 layers with different kernel sizes of 9, 3, and 5 respectively. The number of filters used is 128, 64, and 1. The CNNs have used padding for images of uneven sizes. The activation method used in the layers is ReLu(Rectified Linear Unit) with

$$\Phi(x)=1 \quad x>0 \qquad (2)$$
$$=0 \quad x<0$$

The mean squared error is the function used for loss calculation after each epoch. After training, during testing the degraded images are cropped from M*N into blocks of m*m sizes. Each degraded block is made from batches of size n. The convolutional neural network noise removal is being evaluated based on PSNR(Peak Signal Noise Ratio) and SSIM(Structural Similarity Index). PSNR shows the ratios between the peak signals of power between signal and distorting signals that affect the quality of the signal. SSIM (Structural Similarity Index) is the measure used to find the similarity between images to measure distortions based on the visible structures of the images.



A B C

Figure. 1 ***shows the output of the images after the removal of noise due to low resolution by convolutional neural networks. A represents the original image, B represents the degraded image and C represents the image after the removal of noise by convolutional neural networks***

The PSNR for the images taken from the database as shown in Figure.1 for degraded images are 30 and 44 respectively whereas for the images formed by CNN are 52 and 66 respectively. Even though the changes are merely visible to the naked eye, the implication of changes in power is on a logarithmic scale.

2.2 Haze Removal:- The haze is present in images due to various atmospheric factors like fog, haze, moisture, smoke, etc. The dark channel prior estimate is used for the removal of haze in which the atmospheric light is estimated first. The intensity of pixel x can be calculated as

$$I(x)=J(x)t(x)+A(1-t(x)) \quad (3)$$

I(x) is the intensity of the hazy pixel. J(x) is the intensity of the haze-free pixel. A(x) is the value of Atmospheric light.t(x) is the value for the transmission map. For estimation of atmospheric light, the image is split into blocks of size 15*15 pixels. the dark channel is being calculated by finding out the minimum intensity of all the pixels present in each patch i.e.

$$Dark(J(x))=MIN(r, g, b(x)) \quad (4)$$

The atmospheric light A can be estimated for the whole image by taking into consideration that the whole image has having same constant atmospheric light which is being calculated by sorting the calculated, J dark according to the arguments and taking a block and after the average of dark channels, the atmospheric light is estimated. After the calculation of atmospheric light A, the transmission t(x) can be estimated as

$$t(x)=1-\mu*\min(c)(I^c(y)/A^c) \quad \text{where } \mu=0.95 \quad (5)$$

The final haze-free image can be calculated as

$$J(x)=I(x)-A/\max(t_x,t_0) \quad (6)$$

The haze-free images provide better results with little haze, but provide high brightness with images having adverse effects.

The haze removal from CNN provides a data-driven approach by learning straight from data, CNNs can identify intricate patterns and structures that more conventional approaches would overlook. It also provides end-to-end learning by combining several processes. CNN-based techniques can be trained for haze removal in an end-to-end fashion, streamlining the dehazing process. CNNs produce more realistic and clearer images and frequently surpass conventional dehazing techniques in terms of PSNR, SSIM, and visual quality. However, the haze removal by CNN has some shortcomings like computational complexity for training and deploying deep CNNs requiring significant computational resources and large annotated datasets, and ensuring that CNNs generalize well to different haze conditions and diverse image contents remains a challenge. Figure 2 shows the dehazed images by various dehazing methods by convolutional neural networks.

A B C D E F G

Figure 2. ***Dehazed images by various dehazing methods by convolutional neural networks. A) Input B) Meng C)Berman D) Tang E) Multi-Scale Convolutional Neural Networks F) Multi-Scale Convolutional Neural Networks with Holistic Edges [3]***

2.3 Salt and pepper noise Salt and pepper is a type of noise present in images in which the disturbances are present in the images in the form of speckles that are sparsely spread. It is caused due to sudden disturbance of signals. These disturbances are known as impulse signals. The two methods used to remove salt and pepper are autoencoders and median filters. For denoising to detect salt and pepper with probability ∂ ,∞ if intensity I lie between 0 and ∂ or 255 and 255− ∂ .

In autoencoders, the CNN layers are arranged to have 11 layers in which 9 layers are present having batch normalization along with batch normalization, each layer is paired with Leaky Relu=0.1.

$$\Phi(x)=1 \quad x>0 \quad (7)$$
$$=0.1*x \quad x<0$$

The activation function used in layers to extract features is the sigmoid function with $f(x)=1/1+e^{-x}$. The number of filters used are 64,32,16,8,8,16,32 and 64. After training the images for 50 epochs on these image datasets, the accuracy for the test data set was out to 70%. The resultant test images were proved to have images with less noise or mostly salt and pepper noise removed but with a high reduction in brightness which requires to be enhanced.

While using the median filter, the weights are allocated according to the Euclidean distance from the distorted pixel with the assigned weight $w_{i,}$ to the pixel x. The median value is calculated for substitution. After the calculation, non-linear mapping and reconstruction are performed by the function

$$F(P_i)=MAX(0,W*P_{i-1}+B) \quad (8)$$

The values of W and B are estimated by the mapping function F of parameters. The loss is to be minimized by reducing the mean squared error between images.

The method proposed by Zhang et.al. [15] has several convolutional layers with batch normalization and ReLU activation algorithms that make up the suggested DnCNN. The noise component is predicted using residual learning and subsequently subtracted from the noisy image. Due to the introduction of residual learning, the network's performance and convergence speed are greatly enhanced. Furthermore, FFDNET [16] is made for quick and adaptable image noise reduction. The network can manage different noise levels in a single model since it incorporates a noise level map as an extra input. The network can process images at various resolutions because of its multi-scale structure. This aids in capturing and eliminating salt-and-pepper sounds more effectively. Ren [17] proposed an architecture in which parallel and cascading convolutional neural networks are combined. While the parallel portion records many aspects at various intensities, the cascade portion concentrates on gradually enhancing the image. The network consists of several parallel-operating branches, each of which records a distinct aspect of the noisy image. The final denoised image is created by fusing the outputs. Accuracy and computational efficiency are enhanced by the dual strategy of cascade and parallel processing, which effectively manages salt-and-pepper noise. Noise2Noise presents a novel training paradigm in which the network is trained to recover images from versions that have been corrupted, all without the need for clean targets. When it is difficult to produce clear photographs, this method is quite helpful. The network's conventional U-Net architecture works well for a range of picture restoration applications. Rather than the network structure, the training process is the primary novelty. Noise2Noise [18] shows that clean targets are not necessarily required for training, creating new opportunities for CNNs to be trained in situations where noisy data is the only accessible source. MemNet[19] is a deep CNN with memory blocks. The memory blocks improve the network's capacity to reduce noise by assisting it in maintaining long-term dependencies. MemNet is made up of several memory blocks, each of which has a recursive unit and several convolutional layers. The network can catch and store significant features across several levels because of this topology. The network's capacity to retain picture information while eliminating noise is greatly enhanced by the addition of memory blocks, which makes it an excellent tool for salt-and-pepper noise reduction. Figure 3 shows the architecture of the proposed FFDNet for image denoising. The input image is reshaped into four sub-images, which are then input to the CNN together with a noise level map. The final output is reconstructed by the four denoised sub-images.

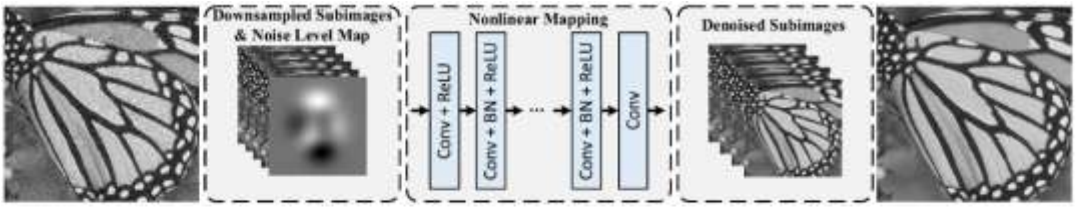


Figure 3. ***The architecture of the proposed FFDNet for image denoising. The input image is reshaped into four sub-images, which are then input to the CNN together with a noise level map. The final output is reconstructed by the four denoised sub-images.[16]***

2.4 Gaussian Blur: Gaussian Blur is a type of blur in which the weights of pixels present in a region are not equal. More weight is provided to the central pixel and less weight is provided to the pixels at the sides. To calculate the blurriness caused by a point, a PSF(Point spread function) is to be calculated. PSF (Point spread function) is defined as the degree to which a point's blurriness spreads across a point of light.

$$g(x,y)= PSF*f(x,y)+ \rho(x,y) \quad (9)$$

Where: g(x,y) is the blurred image, PSF is the Point Spread Function, f(x,y) is the original true image, and ρ(x,y) is the Additive noise. The Gaussian blur can be reduced either by using the Weiner filter or a regulated filter like the Lucy-Richardson Algorithm.

DeblurGAN [20] uses a Generative Adversarial Network (GAN) framework to deblur images. The discriminator network determines which images are generated and which are real. The architecture of the discriminator is a patch-based CNN, and the generator is based on the encoder-decoder architecture with skip connections. The use of adversarial loss encourages the generator to produce more realistic and sharp images. DeblurGAN shows how effective GANs are at producing visually appealing deblurred images and introduces a perceptual loss to improve image quality. Schuler [21] presents a CNN specifically designed for blind image deblurring, meaning the blur kernel is unknown. The network learns to estimate the blur kernel and the latent sharp image jointly. The architecture consists of multiple stages, where each stage refines the blur kernel and the latent image iteratively. The final output is the deblurred image obtained after several iterations. The multi-stage approach effectively addresses the complexity of blind deblurring, achieving superior performance by iteratively refining both the blur kernel and the image. Zhang et. al. [22]]present a deep CNN for image deblurring that uses residual learning and extreme channel prior. The high-frequency information lost to blurring is enhanced by the extreme channel prior. To forecast the difference between the clear and blurry images, the network makes use of a residual learning architecture. The deblurred result is then obtained by subtracting this residual prediction from the blurred image. The network's capacity to recover fine details is greatly improved by the addition of extreme channel prior, which makes it useful for tasks involving both denoising and deblurring. Figure 4 shows the images for deblurring in which (A) Shows the original image, (B) Shows the image that is being blurred due to Gaussian noise, and (C) Shows the image generated after the DeblurGAN algorithm.

Figure 4 . ***Shows the images for deblurring in which (A) Shows the original image, (B) Shows the image that is being blurred due to Gaussian noise, and (C) Shows the image generated after the DeblurGAN algorithm [20]***

3. Results

Table 1. Quantitative Comparison of the State-of-the-art SISR Algorithms for low resolution by average PSNR/SSIM

Method	Params	Set5	Set14	BSDS100	Urban100	Manga109
		PSNR/SSIM	PSNR/SSIM	PSNR/SSIM	PSNR/SSIM	PSNR/SSIM
Bicubic		33.6/0.9299	30.24/0.8688	29.56/0.8431	26.88/0.8403	30.80/0.9339
SRCNN [24]	8K	36.66/0.9542	32.45/0.9067	31.36/0.8879	29.50/0.8946	35.60/0.9663
MemNet [19]	678K	37.52/0.9591	33.08/0.9130	31.08/0.8950	30.41/0.9101	37.27/0.9740
DRCN[25]	1774K	37.63/0.9588	33.04/0.9118	31.85/0.8942	30.73/0.9133	37.55/0.9732
CARN [26]	1592	37.76/0.9590	33.52/0.9166	32.09/0.8978	31.92/0.9256	38.36/0.9765

	K					

To construct a lightweight model, the quantity of network parameters is essential. With fewer parameters, DBDN achieves comparable or higher performance as compared to other state-of-the-art models. On the Manga109 dataset in DBDN, the SSIM goes from 0.9757 to 0.9762 and the PNSR climbs from 37.99 to 38.22 dB. PSNR and SSIM continue to rise after the addition of Feature Fusion units between DCDB, demonstrating the efficacy of FF units.

Table2. Average PSNR and SSIM of dehazed results, and MSE of the estimated transmission maps, on the new synthetic dataset

	He et al.(2011)[3]	Meng et al.(2013)[15]	Berman et al. (2016)[27]	Cai et al.(2016)[28]	MSCNN (Ren) et al.(2016)[3]	MSCNN-HE[3]
PSNR(I)	20.28	16.79	19.26	21.29	21.27	21.32
SSIM(I)	0.80	0.41	0.73	0.84	0.85	0.85
MSE(t)	0.0660	0.0675	0.0549	0.0357	0.0338	0.0332

The projected transmission map is still improved by the holistic edge-guided network. For example, the estimated transmission maps by holistic edges are more accurate and in line with reality, indicating the efficacy of the suggested holistic edge-guided network. Overall, there are fewer color aberrations and better visual clarity in the dehazed images produced by the suggested technique. Additionally, the suggested approach outperforms cutting-edge techniques in terms of PSNR and SSIM metrics, as shown by the qualitative results in Table 2. We compare the suggested approach to state-of-the-art techniques (He et al.2011; Meng et al.2013; Berman et al. 2016; Cai et al. 2016; Li et al.2017; Ren et al. 2016) using SOTS data from the RESIDE dataset (Li et al. 2018).

Table 3. Average PSNR of Results of CBM3D, CDNCNN and FFDNET ON CBSD68 [16]

Methods	σ=15	σ=25	σ=35	σ=50	σ=75
CBM3D	33.52	30.71	28.89	27.38	25.74

CDnCNN [15]	33.89	31.23	29.58	27.92	24.47
FFDNet [16]	33.87	31.21	29.58	27.96	26.24

The performance of different algorithms for salt and pepper noise is detailed in Table 3 and compares the effectiveness of different methods on CBSD68 datasets. It can be noticed that FFDNet performs better than CBM3D on different noise levels as the following quantitative and qualitative evaluation, and has competing performance with CDnCNN.As one can see, Noise Clinic reduces the noise, In terms of visual quality, BM3D, DnCNN, and FFDNet can recover more details and pleasant results. As for the non-blind DnCNN models, they perform on the one hand, the blind DnCNN-B model achieved poor results in excluding the non-AWGN real noise from the given signal. This phenomenon clearly illustrates why the non-blind model has a better generalization capability. model over blind one for managing the trade-off between noise reduction and edge preservation.

Table 4: PSNR and structural similarity measure, mean on the Kohler dataset. Xu et al. and Whyte et al.Some of the non-blind deblurring methods while Sun et al. and Nah et al employ CNN in their approach

	Sun et al.[29]	Nah et al. [30]	Xu et al. [31]	. Whyte et al [32]	DeblurGAN[20]
PSNR	25.22	26.48	27.47	27.03	25.86
SSIM	0.773	0.807	0.811	0.809	0.802

The Kohler dataset is made up of 4 images which are smoothened out using 12 various kernels for each of the images. This is an ideal dataset for assessing the performance of blind deblurring algorithms. The dataset is created by capturing real camera motion at a rate of 30Hz and replaying this motion on a robotic platform, to acquire a sequence of sharp images from a dense sampling of the 6D camera motion path. The results are provided in Table 4.

Object Detection is one of the most extensively researched problems in Computer Vision and has proven to be beneficial in several fields ranging from autonomous cars to security. In the last few years, approaches based on Deep Convolutional Neural Networks have become more popular for image classification. Networks were seen to have outperformed traditional methods in terms of performance-to-noise ratio. However, those networks are trained on limited datasets, and in real-world settings images are often degraded by different artifacts, including motion blur.

4. Conclusion

For low resolution, there is a requirement for an adequate and proper function to calculate loss function for all types of applications. For each specific application, there is a different function. There is a requirement of the CNN model such that a single design will work for all types of applications or a combination of different noises. Removing noise from noisy images, the method is a very complex process because of solves a large sparse matrix, and the space and time complexities are too high to be used in real time. So researching alternate methods for practical applications is highly demanded. The CNNs act as a black box but they should show the proper parameters for a better understanding of deep learning.

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