

IMAGE DENOISING BASED ON AN IMPROVED LEAST-SQUARES GENERATIVE ADVERSARIAL NETWORKS

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ABSTRACT

Digital Image Denoising (noise removal) is one of the fundamental steps taken for the restoration of an actual/ true image from its corresponding contaminated version. Image quality and reliability are vital processes that aid investigations, decisions, and judgments across a wide range of disciplines concerning various application domains like a diagnosis in medicine, digital evidence in multimedia forensics, and court of law, among many others. In the last few decades, it is observed that researchers in this field of Image Processing and Computer Vision adapted the traditional methods or approaches to the removal of noise from images. In recent times, advances in artificial intelligence have led to the adoption and popularity of deep learning methods. The Wasserstein Generative Adversarial Network (WGAN), is one of such popular and better approaches that are used. However, the problem with GAN is that after denoising an image, it introduces another variant of noise that was not originally contained in the given (contaminated) image. Against this backdrop, this study, proffer a solution to image denoising, based on the least-squares generative adversarial networks (LSGAN), using a two-step framework. A Generator model using the SRResnet framework was trained to predict the noise distribution over the input noisy images to ease the vanishing gradient and loss saturation. The Least Squares Method was adapted as the loss function for the discriminator model. From the results of the study, it was discovered that the proposed model showed improved PSNR values when compared with the existing models.; the top three results (from the ten test images for the study) for the proposed model against the existing model gave a PSNR value of 34.40 dB against 32.50dB for the baby image, a PSNR value of 33.73 dB against 31.12dB for the woman image, and a PSNR value of 32.54 dB against 29.10dB for the Zebraimage. Hence, the proposed model successfully improved the quality of images affected by noise without the introduction of any other variant of noise artifact. Keywords— Image Denoising, Image Noise, Image Noise Filtering, Wasserstein GAN. Least Squares GAN

INTRODUCTION

Advances in modern-day technology have resulted in the increase of sophisticated, portable, affordable, and reliable digital acquisition tools (cameras, telescopes, sensors, etc.). As such, there is a significant increase in the adoption of digital tools in various domains like Medicine, Agriculture, Industry, and the military, among many others, which rely on image characterization for scientific and research purposes. Image Denoising is the removal of an unwanted signal (noise) from a given image that interferes with other signals and causes degradation in the quality of the image. Image classification, image segmentation, object recognition, video tracking, and image restoration among many

others, can be carried out through image processing. However, the success of these applications depends largely on how well the preprocessing of the source data is carried out. This makes denoising in image processing a serious affair, for it poses a lot of challenges in the field of image processing (Fan *et al.*, 2019). In real-world applications, denoising is frequently employed in the preprocessing phase (also known as a low-level vision task) before higher-level image segmentation, object detection, and recognition (Pachipulusu,2020). A passive approach to image quality enhancement is to wait for the advances in imaging hardware such as improved sensor technology in acquisition systems (Tyoetal.,2006). Digital cameras have become ubiquitous due to recent advances in hardware and imaging systems (Ngugi *et al.*, 2021). Although hardware advancements have enhanced image quality, image deterioration is inevitable due to a variety of factors like quality acquisition tools, image processing, and compression algorithm among many others (Zhou *et al.*, 2020). These factors are present during the image acquisition process as well as in the post-processing of the image. Image denoising, in order to get exact and high-quality images that are void of noises, is still a topic of interest to an expert in the field of computer vision (Zhang *et al.*, 2017). Again, image denoising is useful in real-time applications, it aids medical image analysis, digital photography, high-resolution images, MRI, remote-sensing, surveillance, and digital entertainment (Pachipulusu,2020). This study addresses image denoising problems, that is the difficulties of removing unknown noises from noisy images.

The rest of this paper is structured as follows. Section 2 overviews the related image denoising techniques. Section 3 describes the method used in the study. Experimental results of the proposed technique are presented in Section 4. A comparative summary is presented in Section 5. Finally, Section 6 concludes this paper and outlines possible directions for future work.

RELATED WORKS

Denoising a digital image is a well-known problem in computer vision which can be classified into traditional and CNN-based methods.

Traditional Image Denoising Methods

Mean Filter

This type of filter is a simple spatial filter that substitutes the center value of the window with the mean values of the total of the window's nearest pixels, including itself (Douglas *et al.*, 2017). It is accomplished using a convolution mask, which produces a weighted sum of the values of a pixel and its neighbors. This is why it is known as a linear filter. The kernel is square in shape. A popular option is a 3x3 mask. The disadvantage of this filter is that it reduces the image's quality and details.

Weiner Filter

This type of filter necessitates the knowledge of the noise as well as the original signal spectra (Cheng *et al.*, 2013). This filtering method is most effective when the underlying signal is smooth. The disadvantage of this filter is that it degrades the image's edges.

Median Filter

The median value of the related window is used to replace the value of a corrupted pixel in a noisy image (Gupta *et al.*, 2011). The value in the middle of any sorted sequence is the median value. Consider the instance when a neighborhood's pixel values are grouped into a series and then sorted in descending or ascending order. The effect of a median filter is difficult to treat analytically.

Weighted Median Filter

The weighted median filter is an enlarged version of the center-weighted median filter (Shafique *et al.*, 2020). The previously designed weighted median filter gives more weight to specific values within the window, whereas the center-weighted median filter gives more weight to the central value of the window (Gupta *et al.*, 2011). This makes it easier to design and implement. The difficulty in changing various elements, such as the number of repeats, is a limitation of this strategy. It also degrades the fine structure of the image, lowering its resolution

Spatial Frequency Domain

In spatial frequency domain denoising, low pass filters (LPF) and the Fast Fourier Transform are used. Denoising is accomplished by setting a cut-off frequency (Gioux *et al.*, 2019). However, this procedure is time-consuming and may result in spurious frequencies in the processed image.

Wavelet Domain

There are two types of Wavelet Domain processes: They are: linear and non-linear. (i) Linear Filters: The Wiener filter is the most commonly used linear filter in this category. In the wavelet domain, the Wiener filter produces the best results. When data corruption can be described as a Gaussian process and the accuracy objective is mean square error, Wiener filtering is used. Wiener filtering, on the other hand, produces a filtered image that is more visually repulsive than the original noisy image. (ii) Non-Linear Threshold Filtering: In this approach, the wavelet transform's property of translating noise in the signal domain to noise in the transform domain is used. Signal energy concentrates on a smaller number of coefficients in the transform domain, whereas noise energy does not. Hard Thresholding is a method for deleting small coefficients while leaving the larger coefficients alone. However, this process produces artifacts, which are erroneous blips.

Data Adaptive Transform

The most commonly used data-adaptive transform method is independent component analysis (ICA), which includes key component analysis, factor analysis, and projection detection (Kuttanet *et al.*, 2021). The ICA method is the most widely used method for dealing with the problem of blind source partitioning. One advantage of using ICA is that it assumes a non-Gaussian signal, which makes denoising images with both non-Gaussian and Gaussian distributions easier. This is because they make use of a sliding window and a sample of at least two image frames from the same scene. The computational cost of ICA-based

techniques is low.

Denoising Based on Convolutional Neural Network (CNN)

REDNET Model

This is also known as Image Restoration Using Convolutional Auto-encoders with Symmetric Skip Connections. Mao *et al.* (2016) describe a CNN- based image denoising method. The network is made up of multiple layers of convolution and deconvolution operators that learn end-to-end mappings from corrupted to original images. While removing corruptions, the convolutional layers record image content abstraction. Deconvolutional layers can be used to upsample feature maps and recover images information. The network promotes learning since it converges much faster and gives better outcomes. This model, however, has two drawbacks, they are: it is time-consuming and it produces a lot of fuzziness.

MWCNN Model

Lui *et al.* (2017) proposed a CNN-based image denoising model that is based on the multi-level wavelet CNN (MWCNN) model. This model allows for a better compromise between receptive field size and computational performance. In the modified U-Net design, the wavelet transform is employed to minimize the size of the feature maps in the contracting subnetwork. To reduce the number of channels in the feature maps, another convolutional layer would be used. The high-resolution feature maps in the expanding subnetwork are then recreated using the inverse wavelet transform. MWCNN's efficacy in image denoising, single-picture super-resolution, and the removal of JPEG image artifacts is demonstrated by the experimental results. However, this model's drawback is that it requires a significant amount of processing time and it also takes an in- ordinate amount of time to train.

PRIDNet Model

In addition, Zhou *et al.* (2020) presented a CNN-based image denoising model that utilizes the Pyramid Real Image Denoising Network which has three stages. To begin with, the noise estimation stage employs a channel attention method to recalibrate the input noise's channel relevance. Secondly, pyramid pooling is used to extract multi-scale features during the multiscale denoising stage. Thirdly, a kernel selection operation is used to adaptively fuse multi-scale features at the feature fusion step. When super-resolving the huge upscaling factors, this model's shortcoming is that it causes loss of finer texture details.

Hybrid of LSGAN, SSI, and L1 loss Model

Furthermore, Ma *et al.* (2020) proposed a Low-Dose CT Image Denoising based on a Generative Adversarial Network with a Hybrid Loss Function for Noise Learning. The model uses the least squares, structural similarity, and L1 losses for low-dose CT denoising. The proposed model shows promising results in terms of visual effects and quantitative measurements on suppressing noise and removing artifacts using a real clinical CT image dataset. However, the proposed model neglected some features.

WGAN Model

In recent times, Zhonget *al.* (2020) proposed a Generative Adversarial network for image denoising using Wasserstein distance as the loss function for training the model. However, the

model still produces another noisy image despite the great improvement in the quality of the image by generating a photo-realistic image.

METHOD

This work in this paper adopts the Least Squares Generative Adversarial Networks (Mao *et al.*, 2017) for noise removal, an extended version of the standard GAN. The model was used to train the Generator on how to deliberately mislead the Discriminator. The Generator received a noisy image as input and was used to come with a solution to an indiscernible image from a ground truth image, whereas the Discriminator received an actual image and a generated image intending to distinguish the actual image from the generated image. As shown in Equations 1 and 2, the competition between Generator and Discriminator for the LSGAN can be expressed as a loss function (for the generator and the discriminator respectively).

$$\min_D V_{LSGAN}(D) = \frac{1}{2} E_{x \sim P_{data}(x)} [(D(x) - j)^2] + \frac{1}{2} E_{x \sim P_z(z)} [(D(G(z)) - i)^2] \dots \dots 1$$

$$\min_G V_{LSGAN} = \frac{1}{2} E_{x \sim P_{data}(x)} [(D(x) - k)^2] + \frac{1}{2} E_{x \sim P_z(z)} [(D(G(z)) - k)^2] \dots \dots 2$$

where *i* and *j* are the labels for the generated data and the actual data respectively, *k* denotes the value that *G* Wants *D* to believe that the generated data coming from *G* to *D* is the actual data. As a result, the authors employ a 0–1 binary coding scheme for *k=j=1* and *i=0*.

Generator Network

The Generator Model Network is the core component of the GAN architecture; it creates the final output from the network. To generate a high-quality photorealistic image, the Generator Model Network would gather more detailed data from neighboring pixels of the image. For this instance, the essential section would use an exceptional architecture with deep convolutional neural networks to create a photo-realistic image. The proposed architecture of the Generator Model Network applies to srresNet (Ledig *et al.*, 2017), and the architecture is depicted in Fig. 1.

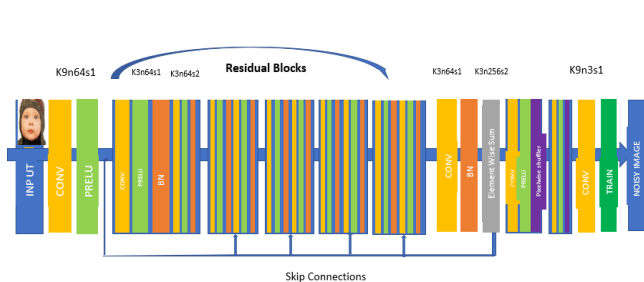


Fig.1: Generator Model

It consists of sixteen Residual Blocks, one convolution block, a bottleneck residual block, and one output layer, with each block containing a PRelu activation (Durejaet *al.*, 2018), a batch

normalization layer (Bjork *et al.*, 2018), and a full convolution layer. By using skip connections, all of the previous layers were fed into each layer (except the last one). This actually prevents gradient vanishing, loss saturation, and improves feature propagation in the networks (Lebrun *et al.*, 2012). From the input noisy image, the convolution layer extracted low-level features. Also, to learn the high-level features, sixteen Residual Blocks were used. Following that, an essential Bottleneck layer was added. It was discovered that A 1x1 convolution layer is ideal for lowering the feature maps used in the input. (Bai *et al.*, 2018). This allows for feature fusion at a low computational cost. The final component is a 3x3 convolution layer that is used to generate output images. The residual correction between the noisy image and the ground truth image was learned by the Generator Network. This aided in the speeding up of the training. The residual learning framework facilitated the training of these networks and allowed them to be significantly deeper, resulting in improved performance. We used 16 residual blocks in the neural network's Generator block, which was upsampled twice. Skip connections, similar to the DenseNet Architecture, were also implemented by the generator. k3n64s1 is an abbreviation for kernels 3, channels 64, and strides 1. We used pixel-to-pixel comparison with the mean squared error function to compare two images. The researchers, on the other hand, used the Perpetual loss function in conjunction with the VGG19 architecture. The study used a feature comparison after passing the image through the VGG19 network rather than a pixel-to-pixel comparison in this loss function

Discriminator Network

The Discriminator Network determines whether an input image is noisy or noiseless. This contributes to the visual appeal of the denoised result. To accomplish this, the Discriminator Network must produce a probability value allotted to the real image data that is as close to one as possible (Noiseless image), and the value of the generated samples is close to zero (Noisy Image). The proposed model's Discriminator Network is similar to that of WGAN. The LeakyReLU (Xu *et al.*, 2015) activation (@ = 0.2) and Layer Normalization (Ba *et al.*, 2016) were included as suggested by (Radford *et al.*, 2015). The proposed model, on the other hand, includes sixteen convolutional layers with 3x3 kernels. The final two layers are fully connected to provide a probability of image generation from the generator model's network or the actual input image. The use of Sigmoid activation was another difference in the final layer and finally the adaption of least squares. Meanwhile, it was not used in their network due to the WGAN-GP. Fig 2 depicts the Discriminator Network's architecture.

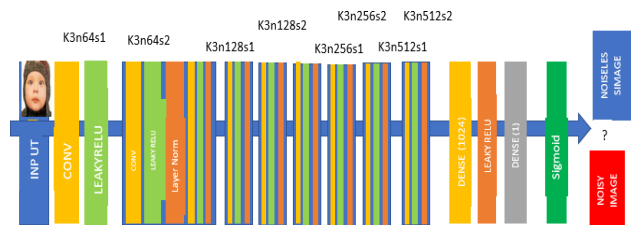


Fig.2: Discriminator Model

For the discriminator, the study used the standard cross-entropy loss function to classify the images as noiseless or noisy images. The activation function employed was used is LeakyRelu, the optimizer for the loss minimization is Adam for both Generator and

Discriminator which gave a stable result when compared to other optimizers

Loss Function

The following issues and difficulties have been encountered by the Standard GAN architecture: A careful coordination of the training level of the Generator Network and Discriminator Network is problematic due to the difficulties required to train and design the model structure. The loss function of the Generator Network and the Discriminator Network, on the other hand, cannot indicate the training process because it lacks meaningful indicators associated with the quality of the generated image. The LSGAN (Mao et al., 2017) was used to ensure that the training was effective. When compared to the WGAN, the LSGAN only makes three simple changes. They are as follows: replacing the last layer of the

Discriminator Network with a previously removed sigmoid function from the WGAN, using the L2 loss function instead of the log loss for proportional penalization, and introducing Weight decay regularization to the bound loss function. Although the LSGAN proposes using the least-squares loss function as an optimization method to train the GAN, there are still differences between mathematics and real-world code implementation. The L2 Loss function is used to minimize the error, which is calculated as the sum of all squared differences between the true and generated values. The Pearson divergence must be satisfied by the L2 loss function (Yamada et al., 2013) to be effective in the application of the network. The working stages of the proposed technique in an algorithmic step are shown in algorithm 1.

Algorithm 1: The Pseudocode of the proposed algorithm (Image Denoising Based of LSGAN)

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1: Procedure LSGAN_DENOISING(X)
2:   N = number of iterations,
3:   I = input image
4:   For I < N do
5:     Sample (X) from the noiseles images
6:     x = addGaussianNoise(X)
7:     Sampley = G(x)
8:     Train Discriminator Network to make X as positive samples and y as negative samples,
       add least squares loss to Discriminator Network
9:     Compute reward r using Discriminator Network to update Generator Network,
       Train Generator Network
10:    Update loss function according to equation (4)
11:  End for
12: End Procedure
    
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EXPERIMENTAL RESULTS

Dataset

This study used DIV2K (Ignatov et al., 2021) images to demonstrate the efficacy of the developed technique. Due to a scarcity of datasets for training and testing single image denoising, the study chose 64x64 image crops extracted from the original images at random for training. Every pixel was normalized to [-1,1]. To generate the noisy images, Gaussian noise with three different levels was added during the training process. The set of input images consists of noisy images, and the set of ground truth images consists of corresponding original images.

Performance Evaluation of Proposed Technique

One metric used to assess the performance of image denoising techniques is the peak signal-to-noise ratio (PSNR). Fig 3 depicts the visual outcome of the proposed techniques when applied to the selected dataset. Table 1 shows the PSNR differences between the original and denoised images. The Gaussian noises with a zero mean and a standard deviation of 30 were used to corrupt the input images.

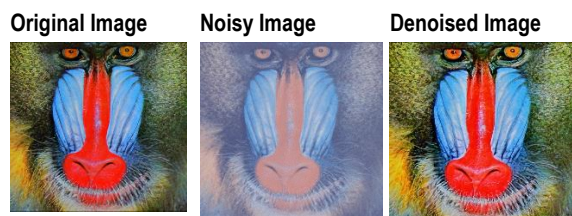




Fig. 3: Visual Result from the proposed technique

Comparison with Other Denoising Techniques

The proposed technique was evaluated with that of Zhong et al. (2020), based on the Peak signal-to-noise ratio (PSNR) which is the most commonly used metric for evaluating the performance of denoising techniques. These techniques were evaluated on the same data set that is used for the initial simulation of the experiment which was discussed in Section 4.1 and the results obtained are summarized in Table 1 and Fig.4

Table1: Comparative Summary

SN	Image	BM3D (Lebrun,2012)	DcNN (Zhang et al., 2017)	WGAN (Zhong et al., 2020)	Proposed System
1	Baboon	23.30dB	24.30dB	23.12 dB	27.18 dB
2	Baby	31.13dB	27.40dB	32.50 dB	34.40 dB
3	Barbara	29.70dB	28.55dB	29.74 dB	32.12 dB
4	Butterfly	26.97dB	28.54dB	28.85 dB	28.43 dB
5	Coastguard	27.86dB	26.08dB	29.54 dB	31.01 dB
6	Comic	25.04dB	29.98dB	26.74 dB	25.89 dB
7	Lenna	29.32dB	28.98dB	28.74 dB	30.20 dB
8	Pepper	29.79dB	28.81dB	26.74 dB	30.34 dB
9	Woman	29.51dB	29.93dB	31.12 dB	33.73 dB
10	Zebra	27.58dB	22.63dB	29.10 dB	32.54 dB

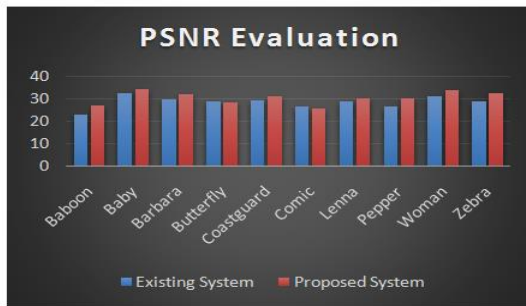


Fig. 4: Performance Evaluation of the existing and the proposed system

CONCLUSION

This paper was successful in developing a new method for image denoising that employs the least-squares generative adversarial network. By utilizing a Residual Block in the Generator Network, the architecture achieves competitive denoising results. Because the Generator Model's Network and the Discriminator Model's Network are competing, the Generator Network generates more photorealistic images. In high-frequency details, the processed images have sharper edges and less blur. In addition to Gaussian noise, the network of this new model can process other types of noise. It is solely based on the training data from the study. In all, this present study has found a way in which the problem that is associated with a WGAN for denoising (when using the model of

Zhong et., 2020) can be solved. This is the major contribution of this study – denoising an image that was unknown on a noisy image, as well as improving the visual quality of the given image.

Few limitations were recorded in the study such as the availability of a development platform and the time taken to train the model. Although the results of this study broke new ground, the model took a larger amount of time for it to be properly trained. This may be due to the robust nature of the architecture. The results showed that the model lacked ground truth images in the training data that corresponded to real noisy images. The study recommends that such areas as ground truth images and actual noisy images; the tuning of hyperparameters and restructuring of the architecture of the newly developed model are all areas that are open or can be considered for further studies

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