Image noise reduction by deep learning methods

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ABSTRACT

Image noise reduction is an important task in the field of computer vision and image processing. Traditional noise filtering methods may be limited by their ability to preserve image details. The purpose of this work is to study and apply deep learning methods to reduce noise in images. The main tasks of noise reduction in images are the removal of Gaussian noise, salt and pepper noise, noise of lines and stripes, noise caused by compression, and noise caused by equipment defects. In this paper, such noises as the removal of raindrops, dust, and traces of snow on the images were considered. In the work, complex patterns and high noise density were studied. A deep learning algorithm, such as the decomposition method with and without preprocessing, and their effectiveness in applying noise reduction are considered. It is expected that the results of the study will confirm the effectiveness of deep learning methods in reducing noise in images. This may lead to the development of more accurate and versatile image processing methods capable of preserving details and improving the visual quality of images in various fields, including medicine, photography, and video.

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1. INTRODUCTION

There are various machine learning methods for removing noise in images, including neural networks, deep learning, image recovery methods [1], and regularization methods [2]–[4]. Neural networks [5] and deep learning, such as autoencoding and convolutional neural networks (CNNs) [6], [7] are often used to remove noise in images. In this paper, the methods considered were trained on clean images, and then used this model to remove noise on noisy images. Raindrops, traces of snow, and dust in the images can be considered as one of the types of noise in the images. They are random white or black spots, and white or gray lines on the background of the image, which can degrade the image quality and make it difficult to analyze. When shooting outdoors, these noises can be especially noticeable on dark backgrounds and at night. To remove such noise in images, various machine learning methods can be used [8]–[10] such as filters, CNNs, and other algorithms. CNNs can be trained on a large number of images with different types of noise to automatically remove noise on new images. There are also noise reduction methods based on statistical analysis that can help in removing such types of noise in images. For example, the histogram method is used to improve image quality by applying histogram alignment. This method changes the brightness or color characteristic of the image in such a way as to obtain a more uniform distribution of pixel values. This method can help to improve the image quality and increase its readability.

Lyu *et al.* [11] present a fast and flexible denoising network (FFDNet), a deep learning model that focuses on fast and flexible image noise reduction. The model provides competitive results in the field of noise reduction while maintaining efficient computing performance. According to Ulyanov *et al.* [12] the concept of using deep neural networks as prerequisites for image reconstruction tasks, including noise suppression, is investigated. The authors demonstrate that a randomly initialized deep neural network (DNN) can capture the basic structure of images and effectively eliminate their noise without the need for additional training data.

Batson and Royer [13] present Noise2Self, a self-supervised learning method for denoising images. The approach leverages the idea that an image can be used as it is noisy label, allowing the model to learn denoising directly from noisy images. Zhai *et al.* [14] addresses the challenges of real-world image denoising, where the noise characteristics are unknown. The authors propose neural adaptation networks (NANs), which can adapt to different noise levels and distributions for effective denoising.

Zhang *et al.* [15] focuses on learning a deep CNN denoiser prior, which can be applied to various image restoration tasks, including denoising. The authors propose a two-stage training framework that incorporates both noisy and clean images to learn effective denoising prior. Sharan *et al.* [16] focuses on video denoising, it presents a deep learning-based approach that can be extended to image denoising. The authors propose a deep video prior, which exploits temporal redundancy in videos to effectively denoise individual frames. These are just a few notable works that demonstrate the effectiveness of deep learning techniques to reduce noise in images. It is important to note that research in this area is constantly evolving, so conducting a comprehensive literature search would allow you to get a more detailed idea of the achievements made in this area.

2. METHOD

The generative model of the attentive generative adversarial network (GAN) combines the ideas of attention and classical GAN architecture. The AttentiveGAN [17], [18] allows the model to focus on specific areas in the data and generate better results. Attention in the context of machine learning refers to a mechanism that allows the model to focus on certain parts of the input data, ignoring the rest. This allows the model to focus on more important details or data areas. An AttentiveGAN usually consists of two main components: a generator and a discriminator, which compete with each other in the learning process. The generator takes random noise or another form of input data as input and generates the generated data. Attention can be applied to the generator so that it can focus on certain areas of data and create more realistic results. The discriminator accepts both real data and generated data from the generator and tries to distinguish them. The task of the discriminator is to distinguish real data from fake data with maximum accuracy. Learning occurs by opposing the generator and discriminator to each other. The architecture of the model for the applied task of this work is shown in Figure 1.

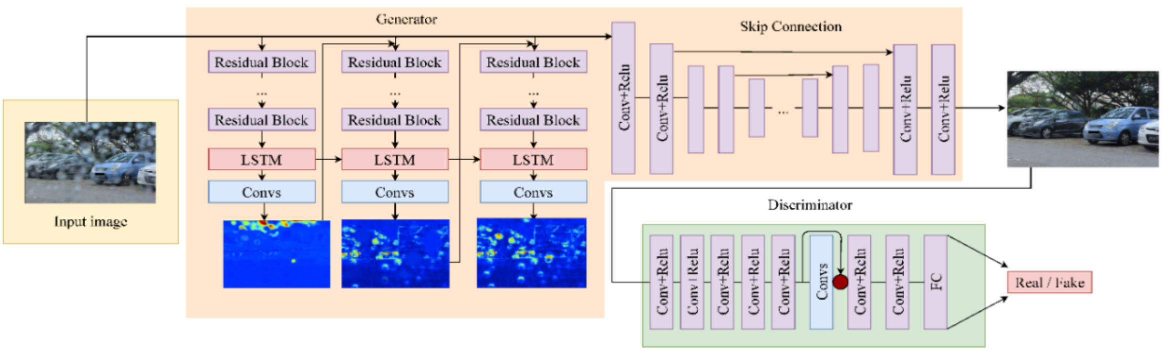

Figure 1. The architecture of the AttentiveGAN model

The effectiveness of using filtering [19] on noisy images depends on several factors, including the type of noise, the noise level, the selected filter, and filtering options. Different types of noise require different filtering methods. For example, for randomly distributed additive noise, such as Gaussian noise, filters based on statistical processing, such as a Gaussian filter or a median filter, are usually effective.

The algorithm for performing Gaussian filtering and the AttentiveGAN (AGAN) model was implemented as follows:

a) Training the AGAN model. First, the AGAN model was trained in pairs of noisy and clean images. The AGAN model generates clean images from noisy inputs.
b) Preparation of a noisy image. The noisy image must be prepared. This may include applying Gaussian filtering to smooth the noise, which can reduce high-frequency noise.
c) Application of the AGAN model. The noisy image is passed through the AGAN model generator. The generator converts the noisy image into a cleaner image using the information obtained during training.
d) Application of Gaussian filtering [20]–[22]. After passing through the AGAN model, the resulting cleaned image is further processed using Gaussian filtering [23]–[25]. This allows you to smooth out the remaining noise and improve the quality of the final image.

3. RESULT AND DISCUSSION

To solve this problem, noisy images with different noise densities were taken, which contain raindrops and traces of dust and snow. The training data set contains 15,314 pre-trained sets of images taken from the Kaggle open-access database. Figure 2 shows noisy images with various types of noise, such as Figure 2(a) traces of dust, Figure 2(b) traces of snow, and Figure 2(c) raindrops.

In this work, when training on pairs of noisy and corresponding clean images, the AttentiveGAN model was used. After the training model, a Gaussian filter was also used. As shown in Figure 3, the results of using the AttentiveGAN model and filtering when removing noise, such as in Figure 3(a) the result of removing traces of dust, in Figure 3(b) the result of removing traces of snow, in Figure 3(c) the result of removing raindrops of the image were impressive. The model was trained to extract important features of the image and restore its clean version, minimizing the effect of noise. Applying a Gaussian filter can effectively reduce image noise, especially when the noise is additive and has a Gaussian distribution. This made it possible to achieve improved image quality with reduced noise.

(a) (b) (c)

Figure 2. Original noisy images (a) dust trails, (b) snow trails, and (c) raindrops

(a) (b) (c)

Figure 3. Processed images (a) the result of removing traces of dust, (b) the result of removing traces of snow, and (c) the result of removing raindrops

In this work, deep learning methods show high efficiency in reducing noise in images. They allow models to automatically study complex dependencies in data and restore clean images with high accuracy. The Terrain model was used for all training images, which made it possible to reduce noise in images of different types. Figure 4 shows the algorithm for executing the AttentiveGAN model using a Gaussian mask.

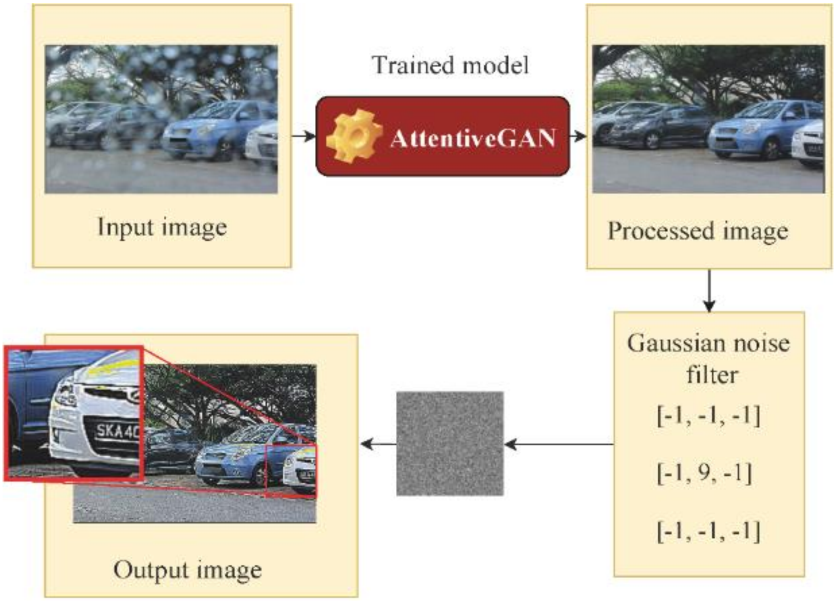

Figure 4. Algorithm for executing the AttentiveGAN model

Gloss, D-loss, and SIM metrics are used in the context of generative-adversarial networks (GAN) to evaluate model performance. The Gloss loss measure (generative loss) evaluates how well the generator in GAN performs its task. The purpose of the generator is to create real examples of data that can pass as real. Gloss allows you to estimate the difference between the generated data and the real data. The lower the G-loss, the better the generator performs its task.

The discriminative loss (D-loss) loss measure evaluates how well the discriminator in GAN distinguishes between generated data and real data. The discriminator in GAN is a model that is trained to classify data as real or generated. D-loss allows you to estimate the difference between the discriminator classification and the actual data labels. The purpose of the discriminator is to be able to accurately distinguish real data from generated data. The lower the D-loss, the better the discriminator performs it is task. The structural similarity index (SSIM) metric is used to measure the similarity between two images. SSIM evaluates the structural similarity between the original and restored images. It takes into account the brightness, contrast, structure, and perception of human vision. SSIM outputs a value from 0 to 1, where 1 means perfect similarity. A high SSIM value as shown in Figure 5 indicates that the restored image is close to the original one in terms of structure.

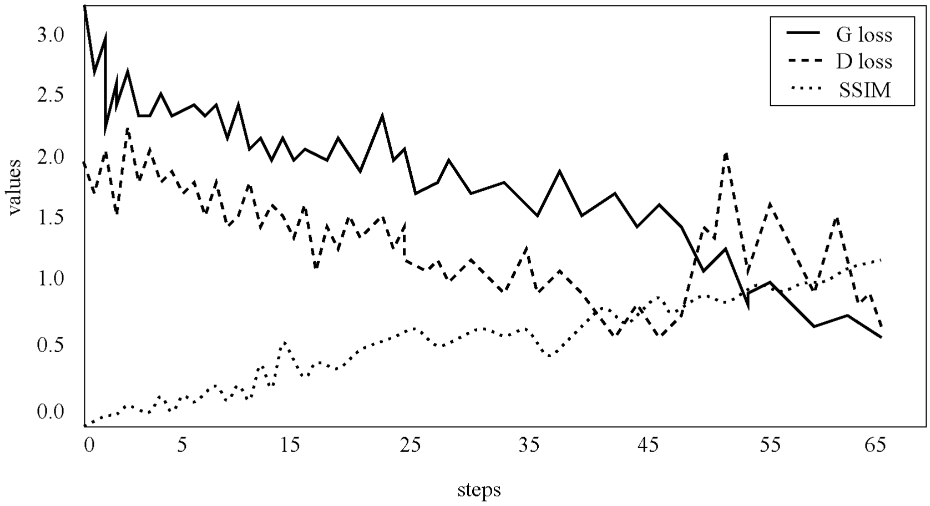

Figure 5. Gloss, D-loss, and SIM loss measure

4. CONCLUSION

In this experiment, the resulting improved images can be effectively used in the future in object recognition. If the background in an image contains noise or unwanted detail, blurring the background helps make objects stand out more. Automated image noise reduction using deep learning techniques can make objects more distinct and easier to recognize.

In the course of the work, it was noted that the effectiveness of deep learning methods for noise reduction depends on the quality of training data, the amount of data, and the choice of model architecture. In this work, noisy images with different noise densities were taken. The optimal result can be achieved with the correct selection of parameters and optimization of the model for a specific type of noise and the desired results. In this work, to achieve a better result, we used a combined model, that is, we trained the data using the Derain model and applied a Gaussian filter. To assess the effectiveness of the model, Gloss, D-loss, and SIM indicators were used, where the SIM value reaches 1, which allows us to evaluate the effectiveness of the deep learning method used.

REFERENCES

[1] J. Tussupov *et al.*, "Applying machine learning to improve a texture type image," *Eastern-European Journal of Enterprise Technologies*, vol. 2, no. 2 (122), pp. 13–18, Apr. 2023, doi: 10.15587/1729-4061.2023.275984.
[2] M. Yessenova *et al.*, "Identification of factors that negatively affect the growth of agricultural crops by methods of orthogonal transformations," *Eastern-European Journal of Enterprise Technologies*, vol. 3, no. 2 (117), pp. 39–47, Jun. 2022, doi: 10.15587/1729-4061.2022.257431.
[3] M. Yessenova *et al.*, "The applicability of informative textural features for the detection of factors negatively influencing the growth of wheat on aerial images," *Eastern-European Journal of Enterprise Technologies*, vol. 4, no. 2(118), pp. 51–58, Aug. 2022, doi: 10.15587/1729-4061.2022.263433.
[4] M. Yessenova *et al.*, "The effectiveness of methods and algorithms for detecting and isolating factors that negatively affect the growth of crops," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 2, pp. 1669–1679, Apr. 2023, doi: 10.11591/ijece.v13i2.pp1669-1679.
[5] Y. Golenko *et al.*, "Implementation of machine learning models to determine the appropriate model for protein function prediction," *Eastern-European Journal of Enterprise Technologies*, vol. 5, no. 4(119), pp. 42–49, Oct. 2022, doi: 10.15587/1729-4061.2022.263270.
[6] A. Paul, A. Kundu, N. Chaki, D. Dutta, and C. S. Jha, "Wavelet enabled convolutional autoencoder based deep neural network for hyperspectral image denoising," *Multimedia Tools and Applications*, vol. 81, no. 2, pp. 2529–2555, Jan. 2022, doi: 10.1007/s11042-021-11689-z.
[7] M. F. C. Aminudin and S. A. Suandi, "Video surveillance image enhancement via a convolutional neural network and stacked denoising autoencoder," *Neural Computing and Applications*, vol. 34, no. 4, pp. 3079–3095, Feb. 2022, doi: 10.1007/s00521-021-06551-0.
[8] R. A. Karim, N. W. Arshad, and Y. A. Wahab, "Contrast modification for pre-enhancement process in multi-contrast rubeosis iridis images," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 21, no. 4, pp. 846–857, Aug. 2023, doi: 10.12928/telkomnika.v21i4.22251.
[9] K. S. Naidana and S. S. Barpanda, "Glaucoma classification using a polynomial-driven deep learning approach," *Bulletin of Electrical Engineering and Informatics (BEEI)*, vol. 12, no. 4, pp. 2245–2261, Aug. 2023, doi: 10.11591/eei.v12i4.4670.
[10] I. A. Hassan, S. A. Ali, and H. K. Obayes, "Enhance iris segmentation method for person recognition based on image processing techniques," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 21, no. 2, pp. 364–373, Apr. 2023, doi: 10.12928/telkomnika.v21i2.23567.
[11] Z. Lyu, Y. Chen, Y. Hou, and C. Zhang, "NSTBNet: Toward a nonsubsampled Shearlet transform for broad convolutional neural network image denoising," *Digital Signal Processing*, vol. 123, Apr. 2022, doi: 10.1016/j.dsp.2022.103407.
[12] D. Ulyanov, A. Vedaldi, and V. Lempitsky, "Deep image prior," *International Journal of Computer Vision*, vol. 128, no. 7, pp. 1867–1888, Jul. 2020, doi: 10.1007/s11263-020-01303-4.
[13] J. Batson and L. Royer, "Noise2self: Blind denoising by self-supervision," in *International Conference on Machine Learning*, 2019, pp. 524–533.
[14] L. Zhai, Y. Wang, S. Cui, and Y. Zhou, "A comprehensive review of deep learning-based real-world image restoration," *IEEE Access*, vol. 11, pp. 21049–21067, 2023, doi: 10.1109/ACCESS.2023.3250616.
[15] K. Zhang, Y. Li, W. Zuo, L. Zhang, L. Van Gool, and R. Timofte, "Plug-and-play image restoration with deep denoiser prior," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, no. 10, pp. 6360–6376, Oct. 2022, doi: 10.1109/TPAMI.2021.3088914.
[16] S. P. Sharan, A. K. Krishna, A. S. Rao, and V. P. Gopi, "RepAr-Net: Re-parameterized encoders and attentive feature arsenals for fast video denoising," in *2022 International Conference on Robotics and Automation (ICRA)*, May 2022, pp. 633–639, doi: 10.1109/ICRA46639.2022.9812394.
[17] H. Wang, H. Zou, and D. Zhang, "Attentive generative adversarial network with dual encoder-decoder for shadow removal," *Information*, vol. 13, no. 8, Aug. 2022, doi: 10.3390/info13080377.
[18] M. Xu, F. Deng, S. Jia, X. Jia, and A. J. Plaza, "Attention mechanism-based generative adversarial networks for cloud removal in Landsat images," *Remote Sensing of Environment*, vol. 271, Mar. 2022, doi: 10.1016/j.rse.2022.112902.
[19] M. Yessenova *et al.*, "Application of informative textural Law's masks methods for processing space images," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 4, pp. 4557–4566, Aug. 2023, doi: 10.11591/ijece.v13i4.pp4557-4566.
[20] X. Zhang, G. Wang, P. Zhu, T. Zhang, C. Li, and L. Jiao, "GRS-Det: An anchor-free rotation ship detector based on Gaussian-Mask in remote sensing images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 59, no. 4, pp. 3518–3531, Apr. 2021, doi: 10.1109/TGRS.2020.3018106.
[21] Q. Chen, C. Li, J. Ning, and K. He, "Gaussian mask convolution for convolutional neural networks," *arXiv preprint arXiv:2302.04544*, 2023.

[22] X. Fan, M. Jiang, and H. Yan, “A deep learning based light-weight face mask detector with residual context attention and gaussian heatmap to fight against COVID-19,” *IEEE Access*, vol. 9, pp. 96964–96974, 2021, doi: 10.1109/ACCESS.2021.3095191.
[23] X. Sun, Z. Yang, C. Zhang, K.-V. Ling, and G. Peng, “Conditional Gaussian distribution learning for open set recognition,” in *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2020, pp. 13477–13486, doi: 10.1109/CVPR42600.2020.01349.
[24] Y. Xie, M. Qiu, H. Zhang, L. Peng, and Z. Chen, “Gaussian distribution based oversampling for imbalanced data classification,” *IEEE Transactions on Knowledge and Data Engineering*, vol. 34, no. 2, pp. 667–679, Feb. 2022, doi: 10.1109/TKDE.2020.2985965.
[25] F. Wang *et al.*, “Design of model predictive control weighting factors for PMSM using gaussian distribution-based particle swarm optimization,” *IEEE Transactions on Industrial Electronics*, vol. 69, no. 11, pp. 10935–10946, Nov. 2022, doi: 10.1109/TIE.2021.3120441.

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