A Review of Image Denoising With Deep Learning

Ahmet Yapıcı
Department of Informatics
Türksat A.Ş.
Ankara, Turkey
ayapici@turksat.com.tr
0000-0002-4274-1064

M. Ali Akcayol
Department of Computer Engineering
Gazi University
Ankara, Turkey
akcayol@gazi.edu.tr
0000-0002-6615-1237

***Abstract*— Satellite images can be corrupted by noise during image capture, transfer or due to bad environmental conditions. In daily life and scientific searches, the need for more accurate images are increasing. However, images are distorted by noise, resulting in lower visual image quality. For this reason, noise removal studies are carried out on images to increase the quality. Until now, various methods have been proposed to decrease noise and each technique have different advantages. This paper, summarizes the studies in the field of noise reduction in video and images and compares the studies with each other.**

Keywords—image denoising, image restoration, video denoising, deep learning-based noise reduction

I. Introduction

Today, video and images are used in various areas of life. Video and image degradation during image transfer and image capture processes is one of the leading problems experienced in computer vision applications. Images encounter noise during acquisition, compression and transmission, resulting in image corruption and data loss. With the presence of noise, image processing stages such as video processing, image analysis and monitoring are adversely affected.

Image denoising is the process of removing noise from an image to restore the true image. Edges and textures are high-frequency components and it is difficult to distinguish noise. During the process of denoising, images may lose some detail. Image denoising is actually a classic problem and although it has been studied for a long time, it is still being studied, because noise removal is an inverse problem and its solution is not unique. Researches show that experiments focus on the case of Additive White Gaussian noise. Different approaches have been used over years to remove noise from video frames and images. Traditional methods can be divided into two categories; spatial domain methods and transformation domain filtering methods. Although most of the traditional methods achieve good performance in image denoising, due to manually adjusted parameters and the need for optimization methods during the training phase, deep learning methods have been recently used. Deep learning methods aim is to obtain the original image by performing statistical calculations. Repetitive calculations increase the success of obtaining the original image. Artificial neural networks have gained popularity due to the improvement in the field. However, studies show that deep learning methods are not flexible against different noise levels and types, and their performance and success rates are not at a sufficient level [1-3].

II. Image Denoising Methods

Satellite images can be corrupted by noise during image capture, transfer or bad environmental conditions. In remote sensing the satellite image data accuracy; depends on the definition of the image area and the accurate determination of the pattern measured on the ground. It is difficult to have reliable information about objects measured on the ground through raw satellite images. While acquiring satellite images, spot or random noise may occur on the image. These noises in the images can be removed with different methods. The main purpose of removing noise in images is to obtain a clean image from noisy data. Noise is expressed by the following equation. Observed noisy image is modeled as $v(i)$, clean image is modeled as $\mathrm{u}(i)$ and additive white Gaussian noise (AWGN) is modeled as $\mathrm{n}(i)$.

$$v(i) = \mathrm{u}(i) + \mathrm{n}(i) \qquad (1)$$

Noises in images are usually expressed as Additive White Gaussian Noise (AWGN) and its standard deviation value is showed as σn . Images can be distorted during image acquisition, coding, transmission, and processing steps. Noise can be estimated with different methods. Since edges and textures are high-frequency components, in the process of denoising, preservation of edge and texture is difficult and images may lose some detail. Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are used to evaluate the accuracy of noise removal process on images [4].

Fig. 1 shows how the noises affect the images. Salt and pepper noise is one of the basic noise type, white and black pixels are sparsely occurs on the images [5]. Speckle, Gaussian and Poisson noise are the other types image noise types. Gaussian noise is generally caused by insufficient illumination. Speckle noise occurs due to ultrasound, laser, sonar or x-rays. Poisson noise occurs due to reflection of light, Salt and pepper noise is caused by surrounding dust or thermal vibration of atoms.

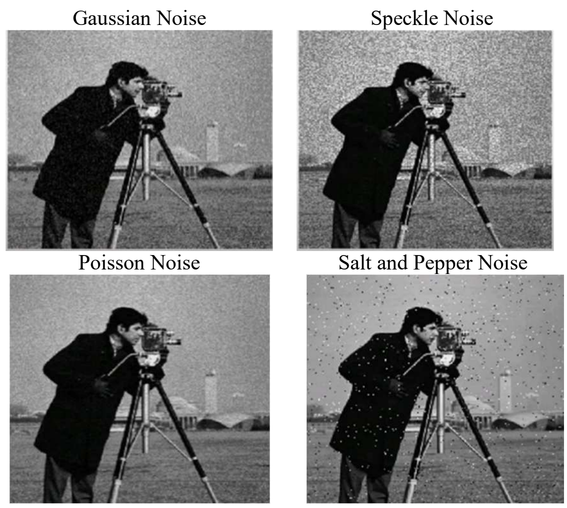

Fig. 1. Example of noise types that distorts the images

2021 2nd International Informatics and Software Engineering Conference (IISEC) | 978-1-6654-0759-5/21/$31.00 ©2021 IEEE | DOI: 10.1109/IISEC54230.2021.9672379

Traditional denoising methods, machine learning methods, deep learning methods and other mathematical methods have been used in the noise removal phase of images over time. Among these methods, traditional noise removal methods and deep learning methods are mostly used and successful results are obtained during image denoising process. These methods can be classified as shown in Fig. 2.

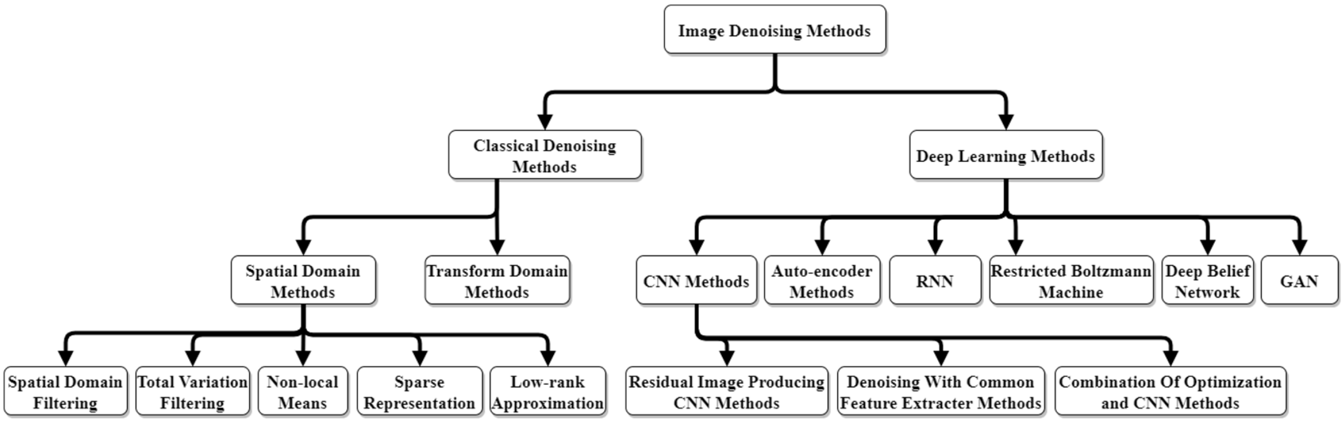

Fig. 2. Classification of traditional and deep learning methods used for image denoising

III. CLASSICAL IMAGE DENOISING METHODS

Classical denoising methods can be categorized two ways; spatial domain filtering and transform domain methods [6].

A. Spatial Domain Methods

In the spatial domain filtering, the image is divided into frames and each frame is filtered separately. Each image on the video is formed by the movement of the previous image, some objects coming out of the screen, and new objects entering the screen. In this method, similar frames in video are found and grouped, and the noise is removed from these frames. Linear filters are used to denoise the image in the spatial domain, but disruptions can occur in image textures. Mean filtering can also be used for Gaussian noise removal [7], but this filter can make the image extremely smooth in high-noise [9]. For this problem, Wiener filtering [9] can be used, but this filter can blur sharp edges in the image. By using nonlinear filters such as median filtering [10] and weighted median filtering [11], noise can be eliminated without the noise level being known in advance. Bilateral filtering [12] is a non-linear filtering method, used to prevent distortion of images. The Total Change Filter is used for image filtering and restoration and to preserve edge values [13]. Non-Local means algorithm aims to prevent the loss of important details and textures, the image is divided into sub-segments at various scales and the average values of the pixels are calculated [14]. In the sparse representation method, the object classes are found by using the sparse representation vector [15]. This method can be used in image processing, makes easier to extract features in the image [16]. Support Vector Machines [17] and Kernel-Based Sparse Representation [18] are important sparse representation approach. Nonlocally Centralized Sparse Representation (NCSR) model is widely used image denoising method, and achieves successful results in reconstruction of both smooth and textured regions [19]. Low-rank approximation model groups similar patches in a matrix. In each column of this matrix, similar patches are kept. The low-order model achieves good results during image denoising [20], but over-smooths image details at very low or very high noise levels.

B. Transform Domain Methods

Transform domain methods were first developed using the Fourier transform. Over time, different transform field methods such as cosine transform, Wavelet-based image denoising methods [21], block matching and 3D filtering (BM3D) [22] have been developed. Independent component analysis [23] and principal component analysis [24] functions are used as transformation tools in the given noisy images. The independent component analysis method has been successfully applied to noise reduction of non-normally distributed data. The disadvantage of this method is the high computational cost and this method requires a noise-free image sample.

IV. DEEP LEARNING METHODS FOR IMAGE DENOISING

Neural networks are preferred for image denoising because of their ease of use, less resource consumption and adaptability to variable noise types. Details of the neural network types are decsribed in the following sections.

A. CNN Methods Used For Image Denoising

In order to reduce noise in images, CNN architectures were used first, among the Neural network-based methods [25]. CNN-based image denoising methods are generally more successful than other methods [26, 27].

a) Residual Image Producing CNN Methods: Unlike the normal CNN methods these methods, produces a noise image instead of parts of the original image. A clear image is obtained by removing the noise image from the original image [28]. In order to create this system, different architectures are designed with combining features from multiple inputs of CNN [29], changing the loss function, changing the depth or width of the CNN architecture [30], using skip links or cascade operations in CNN [31], adding auxiliary plug-ins to CNNs such as activation function, extended convolution, fully connected layer and pooling operations can be applied to increase the success of CNN [32].

b) Denoising With Common Feature Extractor Methods: This method is used together with architectures that have achieved success with the CNN method during noise removal. Wavelet transform and U-network are used in a study [33]. In another study using this method, a combination of CNN and dimensional reduction method is used for high-level noisy images [34]. In another study, a CNN with principal component analysis was used for noise removal in images [35]. In the first step of this architecture, convolution is used to extract features, and Principal Component Analysis is used to reduce the size of the obtained features in the second step. In the third step, convolutions are used to reconstruct a clean image.

c) Combination of Optimization and CNN Methods: Generative Adversarial Networks (GAN) are used for this architecture. To improve denoising success rate, a generative adversarial network with a maximum a posteriori (MAP) method is used to estimate the noise, to inpainting the image and to obtain super resolution image from single image [36]. CNN optimization method is used to improve denoising performance and image denoising success rate [37].

Different methods have been developed using these CNN architectures.

- Denoising Convolutional Neural Networks (DnCNN) are prepared to reduce noise in images and provide a high-performance solution [38]. DnCNN improves transaction performance by reducing the number of data. In CNN networks, the amount of error increases as the depth of the network increases. DnCNN limits the amount of error rate when the depth of network increases.
- Trainable Nonlinear Reaction Diffusion (TNRD) is a non-linear diffusion model used for image restoration [39]. Laplacian Pyramid Super-Resolution Network (LapSRN) is used to create super resolution images. LapSRN has multiple pyramid levels. In this architecture, feature extraction layer and reverse convolutional transformation layers are used together [40].
- As the depth increases in deep convolutional neural networks, performance problems arise. BRDNet aims to combine the two networks to extract more features and increase the width of the network [41].
- The multilevel wavelet-CNN method aims to build faster working denoising model and increase the quality of the image. To achieve this, feature maps are reduced in size and a convolution layer is used to reduce channels. This method is built by modifying U-net structure and a new type of down sampling and up sampling layer is constructed [42].
- Chaining Identity Mapping Modules for Image Denoising architecture contains identity mapping modules [30] different from other architectures. This architecture is composed of dilated kernels [43] and to increase the performance augmentation is used.
- FFDNet can be applied to images with unknown noise levels but this method is successful at higher noise levels [44].
- Efficient Sub-Pixel Convolutional Neural Network (ESPCN) method is used to obtain high resolution images from low resolution images [45]. This method aims to decrease the total amount of computation, processes the feature map with the resolution of the LR image and then up-samples it.

There are other methods developed for image denoising and according to the test results, it has seen that different methods are successful at each noise level and as the image size increases, the processing time of the noise removal methods also increases [46].

B. Autoencoder Methods Used for Noise Reduction on Image

Autoencoders are feedforward neural networks with multiple hidden layers. They are used for dimensionality reduction. During decoding phase image is restored back to the original [47]. Autoencoders are trained using the gradient descent method as in the back-propagation algorithm. By using multiple hidden layers in an autoencoder, large input data can be stored to a smaller code space. Autoencoders are generally used for data size reduction and are also widely used for feature selection, extraction and by customizing the autoencoder architecture they can be used for noise removal.

In an autoencoder architecture, if there are more nodes in the hidden layer than the input layer, the output data becomes equal to the input data called null function. Denoising autoencoder (DAE) solves this problem by randomly deactivating some of the input values.

In the Convolutional DAE method, the encoding and decoding processes are not performed sequentially, the decoding process can be combined with encoding. In this way, important data can be used as output without compression. In a study convolutional denoising autoencoders are used to remove noise in medical images [48].

Denoising autoencoders (DAE) are trained to obtain clean data and to solve the null function, in Variational denoising autoencoder (VAE) architecture noise is injected to original data. This method is used to obtain clear images from distorted images and to classify images [49].

C. RNN

Recurrent Neural Network (RNN) architecture uses back propagation algorithm, unlike feed forward networks. In this method, error rate is reduced during the training of the network. RNN is also used for video denoising [50], in another study RNN is used for the removal of noise in ECG signals [51]. Long Short-Term Memories contain doors to make new decisions with previous data, use data in the future, and store the data. However, they require more processing and more memory. The Long Short-Term Memory method was used for the removal of noise in computerized lung tomography images [52].

D. Restricted Boltzmann Machine

RBM is two-layer neural networks. In high-noise images, the use of deep RBM networks produces better results [53].

E. Deep Belief Networks

Deep Belief Networks are effective way for feature extraction. Since the Restricted Boltzmann Machines have a two-layer structure, deep belief networks have been created to deepen this network. In Deep Belief Networks, the connections in the upper layers are non-directional, and the connections in the lower layers are directional [54]. Deep Belief Networks are also used for denoising images. In a study, successful result was obtained by applying Deep Belief Networks to the MNIST data set corrupted by additional white gaussian noise [55].

F. GAN

GANs are generative models, these models are composed of the generator model and the discriminator model. In an image denoising study GAN method is used to obtain clean images [56]. Other study generates clean images if there is no paired training data; a GAN model is used to estimate the noise distribution and a deep Convolutional Neural Network (CNN) is used for denoising [57]. GAN models are successful in blind image denoising problems [58].

V. DEEP LEARNING METHODS FOR VIDEO DENOISING

During video denoising, video images are decomposed into frames and image denoising techniques are applied to frames to reduce noise in the video [59]. The methods that have been successful in removing noise in images have also been adapted to videos. For example, BM3D and NLB methods are adapted to video and VBM4D and VNLB are built for video denoising. DVDNet method uses traditional denoising methods and CNN together for video denoising [60]. Success criteria in video denoising is closely related to; absence of the blurry images, preservation of image details, image denoising time period and closeness to the original image.

VI. DISCUSSION

In this article, deep learning methods and traditional methods applied in the noise removal stage are mentioned. Due to the complexity of the image denoising process and the need for the removing these noises quickly and accurately, researches in this area are still ongoing.

A. Challenges and Current Techniques in Noise Reduction

Although most of the traditional methods used in the image denoising stage achieve a very good performance but they have disadvantages such as having manually adjusted parameters and needing optimization methods in the training stage. Different deep learning methods are used to remove noise on the image. Artificial neural networks are preferred for the noise reduction in images because of their ease of use, less resource consumption and adaptability to variable noise types. It has been seen that the use of the following techniques in convolutional neural network architectures has a positive effect on the image denoising success rate:

1) By expanding the receiving area, networks can gain more information. This architecture needs more computer performance, to solve this problem, dilated convolutions can be used, which are effective in providing more edge information.

2) The selected loss function affects the training time. The loss function should be preferred in a way that shortens the training time.

3) Since deep networks provide better denoising results, residual networks can be preferred to improve performance in deep networks.

4) Using other techniques within the CNN architecture provides better results. The use of wavelet transform inside the U-net network is an example of such use.

5) Using the training data, more sample data can be generated using transformation techniques and changing colors. Data augmentation enables training with the more samples.

6) Using traditional methods and deep learning methods together positively affects the success of noise removal on image and video.

B. Conclusion

In recent studies, it has been observed that a single deep learning method cannot achieve success in different noise types and different video resolutions, and it is seen that different deep learning methods are successful for different noise levels and different resolution images. Although many studies have been carried out on the removal of additional white gaussian noise, due to the complexity of the noise in real images and the lack of original images, correct comparisons cannot be done on images. Networks with a deeper architecture achieve better results during image denoising. However, deeper networks consume more memory, resulting in overfitting and vanishing gradient problem. Additional white gaussian noises sometimes fail to sample real-life noises, resulting in insufficient training data.

In future studies, it is necessary to investigate how to remove the noise in real-life images and to train deep learning models without having the original image pairs and prior knowledge of noise model. In future studies, deep learning architectures should be built to increase efficiency of denoising values at different noise levels, considering the system resources used, training time and proximity to the original image.

[1] N. Abiri, B. Linse, P. Edén, and M. Ohlsson, “Establishing strong imputation performance of a denoising autoencoder in a wide range of missing data problems”, Elsevier, Neurocomputing, 2019, pp. 137-146.

[2] Y. Chang, “Research on demotion blur image processing based on deep learning”, J. Vis. Commun. Image R. Elsevier, vol. 60, 2019, pp. 371–379.

[3] A. Erol, M. Gürbüz, and A. Gangal, “Video Görüntülerindeki Periyodik Gürültülerin Yok Edilmesi”, Researchgate, 2016, pp. 535-537.

[4] D. Liu, D. Li, and H. Song, “Image Quality Assessment Using Regularity of Color Distribution”, IEEE Access, vol. 4, 2016, pp. 4478-4483.

[5] W. K. Pratt, Digital Image Processing, Fourth Edition, John Wiley & Sons Inc, 2007.

[6] M. Diwakar, and M. Kumar, “A review on CT image noise and its denoising”, Biomed Signal Process Control, Dehradun, pp. 73–88, April 2018.

[7] X. Weizheng, X. Chenqi, J. Zhengru, and H. Yueping, "Digital Image Denoising Method Based on Mean Filter, International Conference on Computer Engineering and Application (ICCEA), 2020, pp. 857-859.

[8] S. Tania, and R. Rowaida, “A Comparative Study of Various Image Filtering Techniques for Removing Various Noisy Pixels in Aerial Image”, International Journal of Signal Processing, Image Processing and Pattern Recognition, 9(3), 2016, pp. 113-124.

[9] W. K. Pratt, “Generalized Wiener Filtering Computation Techniques”, IEEE Transactions on Computers, C-21(7), 1972, pp. 636-641.

[10] Y. Lee, and S. Kassam, “Generalized median filtering and related nonlinear filtering techniques”, IEEE Transactions on Acoustics, Speech, and Signal Processing, 33(3), 1985, pp. 672-683.

[11] L. Yin, R. Yang, M. Gabbouj, aand Y. Neuvo, Weighted median filters: a tutorial, IEEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing, 43(3), 1996, pp. 157-192.

[12] C. Tomasi, R. Manduchi, "Bilateral filtering for gray and color images", Sixth international conference on computer vision IEEE, Bombay, India, pp. 839–846, January 1998.

[13] I. R. Leonid, O. Stanley, and F. Emad, "Nonlinear total variation based noise removal algorithms", Physica D, Nonlinear Phenomena, Volume 60, Issue 1-4, 1992, pp. 259-268.

[14] A. Buades, B. Coll, and J. M. Morel, "A non-local algorithm for image denoising", IEEE computer society conference on computer vision and pattern recognition, IEEE, San Diego, 2(2), 2005, pp. 60–65.

[15] J. Wright, A.Y. Yang, A. Ganesh, S. S. Sastry, and Y. Ma, "Robust face recognition via sparse representation", IEEE Transactions on Pattern analysis and Machine Intelligence, 31(2), 2009, pp. 210-227.

[16] W. Deng, J. Hu, and J. Guo, "Extended SRC: Undersampled face recognition via intraclass variant dictionary", IEEE Trans. Pattern Anal. Mach. Intell, 34(9), 2012, pp. 1864-1870.

[17] L. Zhang, and W. Zhou, "On the sparseness of 1-norm support vector machines, Neural Network"s, 23(3), 2009, pp. 373-385.

[18] S. Gao, I. W. H. Tsang, and L. T. Chia, "Kernel sparse representation for image classification and face recognition", 11th Eur. Conf. Comput. Vis., 6314, 2010, pp. 1-14.

[19] S. Xu, X. Yang, and S. Jiang, "A fast nonlocally centralized sparse representation algorithm for image denoising, Signal Processing", Volume 131, 2017, pp. 99-112.

[20] L. Fan, F. Zhang, and H. Fan, "Brief review of image denoising techniques", Visual Computing for Industry, Biomedicine, and Art, 2019, 2(7).

[21] M. Bhuiyan, M. Ahmad, and M. Swamy, "Wavelet-based image denoising with the normal inverse Gaussian prior and linear MMSE estimator", Iet Image Processing, volume 2, 2008, pp. 203-217.

[22] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, "Image denoising by sparse 3-D transform-domain collaborative filtering", IEEE Trans Image Process, 16(8), 2007, pp. 2080–2095.

[23] A. Hyvarinen, E. Oja, P. Hoyer, and J. Hurri, "Image feature extraction by sparse coding and independent component analysis", 14th international conference on pattern recognition. IEEE, Brisbane, 1998, pp. 1268–1273.

[24] I. Jolliffe, Principal component analysis, 2. Baskı, New York, Springer-Verlag, 2005.

[25] V. Jain, and H. Seung, "Natural Image Denoising with Convolutional Networks", Advances in Neural Information Processing Systems, 2009, pp. 769–776.

[26] J. Kim, J. K. Lee, and K. M. Lee, "Accurate image super-resolution using very deep convolutional networks", IEEE conference on computer vision and pattern recognition, Las Vegas, pp. 1646–1654, June 2016.

[27] X. Wang, K. Chan, K. Yu, C. Dong, and C. C. Loy, "EDVR: Video restoration with enhanced deformable convolutional networks", IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, 2019, pp. 1954-1963.

[28] C. Tian, Y. Xu, L. Fei, and K. Yan, "Deep Learning for Image Denoising: A Survey", ICGEC 2018 Advances in Intelligent Systems and Computing, Singapore, vol 834, 2019.

[29] W. Jeon, W. Jeong, K. Son, and H. Yang, "Speckle noise reduction for digital holographic images using multi-scale convolutional neural networks", Optics Letters, 43(17), 2018, pp. 4240–4243.

[30] S. Liu, and W. Deng, "Very deep convolutional neural network based image classification using small training sample size", IAPR Asian Conference on Pattern Recognition (ACPR), 2015, pp. 730-734.

[31] C. Chen, Z. Xiong, X. Tian, and F. Wu, "Deep boosting for image denoising", European Conference on Computer Vision (ECCV), Munich, Germany, pp. 3–18, September 2018.

[32] F. Yu, V. Koltun, and T. Funkhouser, "Dilated residual networks", Computer Vision and Pattern Recognition (CVPR), 2017. arXiv: 1705.09914.

[33] P. Liu, H. Zhang, K. Zhang, L. Lin, and W. Zuo, "Multi-level wavelet-cnn for image restoration", IEEE Conference on Computer Vision and Pattern Recognition Workshops, Salt Lake City, Utah, pp. 773–782, June 2018.

[34] Y. Q. Zhao, and J. Yang, "Hyperspectral image denoising via sparse representation and low-rank constraint", IEEE Transactions on Geoscience and Remote Sensing, 53(1), 2015, pp. 296-308.

[35] A. T. Bui, J. K. Im, D. W. Apley, and G. C. Runger, "Projection-free kernel principal component analysis for denoising", Elsevier Neurocomputing, 357, 2019, pp. 163-176.

[36] S. Cha, T. Park, B. Kim, J. Baek, and T. Moon, "GAN2GAN: Generative Noise Learning for Blind Denoising with Single Noisy Images", International Conference on Learning Representations (ICLR), 2021.

[37] Z. Luo, S. Chen, Y. Qian, "A Deep Optimization Approach for Image Deconvolution", Computer Vision and Pattern Recognition, 2019, arXiv:1904.07516.

[38] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, "Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising", IEEE Transactions on Image Processing, 26(7), 2017, pp. 3142-3155.

[39] Y. Chen, and T. Pock, "Trainable nonlinear reaction diffusion: A flexible framework for fast and effective image restoration", IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(6), 2016, pp. 1256-1272.

[40] W. S. Lai, J. B. Huang, N. Ahuja, and M. H. Yang, "Deep Laplacian Pyramid Networks for Fast and Accurate Super-Resolution", 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR, Honolulu, 5835-5843, June 2017.

[41] C. Tian, Y. Xu, W. Zuo, "Image denoising using deep cnn with batch renormalization", Neural Networks 121, 2020, pp. 461–473.

[42] P. Liu, H. Zhang, K. Zhang, L. Lin, and W. Zuo, "Multi-level Wavelet-CNN for Image Restoration", IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Salt Lake City, 773-782, June 2018.

[43] S. Anwar, C. P. Huynh, and F. Porikli "Chaining identity mapping modules for image denoising", 2017. arXiv:1712.02933.

[44] G. Anandbabu, N. Merajothu, and G. Kirankumar, "Convolutional neural network based image denoising for better quality of images", International Journal of Engineering and Technology(UAE), 7, 2018, pp. 356-361.

[45] W. Shi, J. Caballero, F. Huszar, J. Totz, A. Aitken, R. Bishop, D. Rueckert, and Z. Wang, "Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network", IEEE conference on computer vision and pattern recognition, Las Vegas, pp. 1874-1883, June 2016.

[46] T. Chunwei, F. Lunke, Z. Wenxian, X. Yong, Z. Wangmeng, and L. Chia-Wen, "Deep Learning on Image Denoising: An Overview", Neural networks: the official journal of the International Neural Network Society, 2020, pp. 251-275. arXiv:1912.13171.

[47] Y. Bengio, "Learning deep architectures for AI, Foundations and Trends in Machine Learning", 2(1), 2009, pp. 1–127.

[48] L. Gondara, "Medical Image Denoising Using Convolutional Denoising Autoencoders", IEEE International Conference on Data Mining Workshops, ICDMW, 12-15 Aralık, Barcelona, pp. 241-246i December 2017.

[49] A. Creswell, and A. A. Bharath, "Denoising Adversarial Autoencoders", 2018, arXiv:1703.01220v4.

[50] X. Chena, L. Songa, and X. Yanga, "Deep RNNs for Video Denoising", SPIE 9971, Applications of Digital Image Processing, 2016.

[51] K. Antczak, "Deep Recurrent Neural Networks for ECG Signal Denoising", 9(1), 2018, pp. 135. arXiv:1807.11551

[52] R. Rajeev, J. Samath, and N. Karthikeyan, "An Intelligent Recurrent Neural Network with Long Short-Term Memory (LSTM) BASED Batch Normalization for Medical Image Denoising", Journal of Medical Systems, Springer Science, 43(8), 2019, pp. 234.

[53] K. Cho, "Boltzmann Machines for Image Denoising", Artificial Neural Networks and Machine Learning – ICANN, Springer, Sofia, pp. 611-618, September 2013.

[54] G. E. Hinton, and R. R. Salakhutdinov, "Reducing the Dimensionality of Data with Neural Networks", 313(5786), 2006, pp. 504–507.

[55] M. Keyvanrad, M. Pezeshki, and M. Homayounpour, "Deep Belief Networks for Image Denoising", 2013. arXiv:1312.6158.

[56] Z. Wang, L. Wang, S. Duan, and Y. Li, "An Image Denoising Method Based on Deep Residual GAN", J. Phys. Conf. Ser., 1550, 032127, 2020.

[57] J. Chen, H. Chao, and M. Yang, "Image blind denoising with generative adversarial networkbased noise modeling", IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018, pp. 3155–3164.

[58] C. Liu, W. T. Freeman, R. Szeliski, and S. B. Kang, "Noise Estimation from a Single Image", IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06), 2006, pp. 901-908.

[59] C. Wang, S. K. Zhou, and Z. Cheng, "First image then video: A two-stage network for spatiotemporal video denoising", 2020. arXiv:2001.00346.

[60] M. Tassano, J. Delon, and T. Veit, "Dvdnet: A fast network for deep video denoising", International Conference on Image Processing (ICIP), IEEE, Taipei, pp. 1805–1809, September 2019.