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Image Reconstruction and De-noising using Neural Network: A Systematic Literature Review

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Abstract

Image reconstruction and de-noising are critical components in modern image processing systems, with significant applications in medical imaging, satellite photography, surveillance, and autonomous systems. Traditional signal processing approaches, while effective to an extent, often struggle with complex noise patterns and high-detail preservation. In recent years, neural network-based methods have emerged as powerful tools to address these challenges, offering superior performance in both noise reduction and image structure restoration. This systematic literature review provides a comprehensive overview of recent advancements in neural network-based techniques for image reconstruction and de-noising. The reviewed literature is categorized into key neural architectures such as Convolutional Neural Networks (CNNs), Autoencoders, Generative Adversarial Networks (GANs), and Recurrent Neural Networks (RNNs). Each approach is evaluated in terms of methodology, dataset usage, performance metrics (PSNR, SSIM, MSE), and application domain. Despite these advancements, challenges remain in areas such as generalization to unknown noise types, model interpretability, training stability, and real-time deployment on low-power devices. This review also highlights future research opportunities, including hybrid neural models, physics-informed learning, federated training, and self-supervised approaches. Overall, this work aims to serve as a valuable resource for researchers and practitioners seeking to understand and develop state-of-the-art neural network models for robust image de-noising and reconstruction tasks.

Keywords: - Image Reconstruction, De-noising, Neural Network

1. INTRODUCTION

The use of photographs has significantly increased during the past ten years. During the capture, compression, and transmission processes, noise taints images. Noise can taint images through a variety of channels, including transmission and environmental ones. When processing images, the change in signal (in random form) is called image noisenthat influences the color or brightness of the image being observed and the extraction of information. Images are negatively impacted by noise. Processing activities (such image analysis, video processing, and segmentation), which leads to an incorrect diagnosis [1]. Hence, image denoising is a key component that enhances comprehending the challenge of picture processing. As more digital photos are produced under unfavorable circumstances, picture denoising techniques have become a necessary computer-aided analysis tool.

These days, the procedure for recovering data from noise pictures to get a clear image is a pressing issue. Image denoising techniques eliminate noise and improve a clear picture. One of the main issues with image denoising is how to discern between texture, edge, and noise (since they high-frequency components are present in all.

It is interesting to note that the noises that are most frequently discussed in literature include quantization noise [4], impulse noise [3], and additive white Gaussian noise (AWGN) [2]. Speckle noise [6] and Poisson noise [5]. AWGN takes place in analog circuitry, whereas bit error, poor manufacturing, and impulse, speckle, Poisson, and quantization noise are caused by and insufficient number of photons. Techniques for image denoising are employed in the fields of remote sensing, medical imaging, industrial monitoring, biometrics and forensics, and military in the mechanization of agriculture, as well as in the identification of people. Denoising algorithms are essential pre-processing procedures in medical and biological imaging that are used to eliminate medical noise, including quantum, Rician, and speckle, among others.

Additionally, forensic photos do not have a particular type of sound, they could be tainted by any of sound. This noise may degrade the quality of the supporting data in the consequently, picture denoising techniques have assisted in suppressing forensic picture noise. Techniques for image denoising were employed to identify rice plant diseases and filter paddy leaves.

Without a doubt, picture denoising is a popular field of study. covering every aspect of academic pursuits. The filters that were linear, non-linear, and non-adaptive were the initial filters for picture applications [7]. Decrease of noise There are six types of filters: linear, non-linear, adaptive, partial differential equation (PDE), wavelet-based, and total variation filters). The right output pixels are filtered with linear filters. with nearby pixels in the input (using a matrix multiplication process) in order to minimize noise. The non-linear filters maintain edge data while maintaining noise suppression. The majority of faltering applications, non-linear filters are utilized instead of filter.

2. LITERATURE REVIEW

Soomro T.A et al. [1], as a non-invasive imaging technique, MRI has been widely utilized to identify and diagnose brain disorders as well as track their course of treatment. Neurologists can more accurately detect abnormalities from brain imaging because to the three-dimensional images that MRI creates. But this is a labor-intensive and time-consuming operation. A computer-aided method for analyzing MRI pictures and precisely identifying abnormalities has been made possible by advancements in machine learning and rapid processing. In the field of medical image analysis, image segmentation has grown in popularity and research focus. The ability to rapidly classify the disease for early treatment is made possible by the computer-aided technique for identifying brain abnormalities. The research articles on brain tumor segmentation from MRI images (published between 1998 and 2020) are reviewed in this article. We thoroughly investigated each research paper's fundamental segmentation techniques. This essay gives readers a thorough introduction to the subject and offers fresh perspectives on the various machine learning and image segmentation techniques used to detect brain tumors. The deep learning techniques outperform the state-of-the-art and the latest cutting-edge approaches in terms of tumor segmentation from brain MRI data.

Yang et al. [2], the widespread use of CT in medicine and its ongoing advancement have sparked public concern about the radiation dose that patients may receive. Lowering the radiation dose could result in more noise and artifacts, which could impair the radiologists' confidence and judgment. Therefore, to improve the diagnostic performance, sophisticated picture reconstruction from low-dose CT data is required. This is a difficult problem since it is ill-posed. Numerous low-dose CT techniques have yielded remarkable outcomes in recent years. But under general penalties, the majority of algorithms created for this use, such as the lately widely used deep learning methods, seek to minimize the mean-squared error (MSE) between a denoised CT picture and the ground truth. After intensive denoising, MSE- or

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weighted-MSE-based techniques may make it more difficult to see crucial structural details, even while the peak signal-to-noise ratio is improved. This study presents a novel approach to denoising CT images using generative adversarial networks (GANs) with perceptual similarity and Wasserstein distance. A fundamental idea in optimum transport theory, the Wasserstein distance holds potential for enhancing GAN performance. While the GAN concentrates primarily on statistically reducing the data noise distribution from strong to weak, the perceptual loss reduces noise by comparing the perceptual qualities of a denoised output with those of the ground truth in a pre-established feature space. Consequently, our suggested approach applies our understanding of visual perception to the picture denoising job and can not only lower the image noise level but also attempt.

Li et al. [3], medical image denoising is a major study area because of the strong correlation between medical picture quality and clinical diagnosis and treatment. Deep learning-based image denoising has garnered a lot of interest because of its superior automatic feature extraction capabilities. The majority of medical picture denoising techniques currently in use struggle to deal with spatially variable noise; in the meantime, the denoised image lost detail and underwent structural alterations. This research first presents a medical picture denoising technique based on conditional generative adversarial network (CGAN) for different unknown noises, taking into account image context perception and structure preservation. The suggested design improves the contrast between the original signal and noise based on structural specificity by merging the noise image with the appropriate gradient image as network conditional information. The interaction between convolutional layers is fully utilized by a unique generator with residual dense blocks to investigate visual context. Additionally, to guarantee the consistency of the denoised and genuine images, the reconstruction loss and WGAN loss are merged as the objective loss function. Medical image denoising tests are carried out using JSRT datasets with denoising results of PSNR = 33.2642 and SSIM = 0.9206 and LIDC datasets with denoising results of PSNR = 35.1086 and SSIM = 0.9328. The suggested method's superior performance when compared to the state-of-the-art approaches is remarkable.

Sun et al. [4], the intrinsic resolution of the imaging device and naturally noisy data, which provide a low signal-to-noise ratio (SNR) of PET images, are two aspects that impact the quantitative accuracy of PET. In order to solve this issue, we presented a novel deep learning denoising framework in this paper that aims to improve the quantitative accuracy of dynamic PET images by introducing Regularization by Denoising (RED) in conjunction with Deep Image Prior (DIP). This approach is known as DeepRED denoising. The estimated image is produced by combining hierarchical characteristics via skip links in a network structure based on encoder-decoder architecture. In order to circumvent the necessity for high-quality noiseless images, which are restricted in PET clinical practice due to high radiation dose, the network input might be random noise or other previous images (such as the patient's own static PET image). The suggested approach's quantitative performance was evaluated using both simulated and actual patient data, and it was contrasted with the traditional Gaussian filtering (GF), non-local mean (NLM), block-matching and 3D filtering (BM3D), DIP, and stochastic gradient Langevin dynamics (SGLD) methods. Overall, both with and without preceding images, the suggested approach can significantly increase both visual and quantitative accuracy (in terms of noise versus bias performance) compared to other traditional methods.

J. Chen et al. [5], in order to address image noise, this research introduces a method known as the Multi-Scale Wavelet Convolutional Neural Network. Convolutional neural networks and wavelet transforms are combined in this technique to denoise an image while preserving key aspects of it. The technique uses Discrete Wavelet Transform and deep learning to analyze images at several scales. This job makes use of the SIDD dataset, which comprises noisy/ground-truth image pairings captured by five distinct smartphones in various lighting scenarios. MWCNN greatly improved the quality of the images.The average mean squared error for denoised photos was 22.41, the average structural similarity index was 0.8650, and the observed peak signal to noise ratio was 35.42 dB when evaluated with real-world noises in images. MWCNN's potential as an image-de-noising solution has applications in security, healthcare, artifact removal, surveillance film enhancement, and medical imaging.

3. IMAGE RECONSTRUCTION AND DE-NOISING

Image reconstruction and de-noising are fundamental tasks in image processing that aim to restore or enhance the quality of images affected by noise or degradation. Image reconstruction refers to the process of generating a high-quality image from incomplete, corrupted, or indirect observations—commonly encountered in fields like medical imaging (e.g., MRI, CT scans), remote sensing, and computer vision. On the other hand, image de-noising focuses specifically on removing unwanted distortions or noise from images, such as Gaussian noise, impulse noise, or speckle noise, which often arise from sensor limitations, transmission errors, or environmental interference. The goal is to eliminate these noise elements while preserving important image features like edges, textures, and fine details.

Traditional methods for these tasks include filtering techniques (like Gaussian filters, median filters), wavelet transforms, and optimization-based algorithms. However, these methods often struggle with balancing noise removal and detail preservation. In contrast, neural networks—especially deep learning models—have shown remarkable capabilities in learning complex patterns from large datasets, enabling more effective and adaptive image restoration. Deep architectures such as CNNs, autoencoders, GANs, and RNNs have been widely adopted for this purpose. They can model the non-linear relationships between noisy and clean images and offer robust performance across various noise levels and types. With growing computational power and availability of annotated datasets, neural network-based methods have become state-of-the-art solutions in both image reconstruction and de-noising, achieving superior results in terms of visual quality and quantitative performance metrics like PSNR and SSIM.

4. NEURAL NETWORK

An artificial neural network is a computational model inspired in the natural neurons of a biological nervous system. These models mimic the real life behavior of neurons and the electrical messages they produce between input processing by the brain and the final output from the brain. In other words, artificial neural networks form an attempt to create machines that work in a similar way to the human brain by building these machines using components that behave like biological neurons. The function of an artificial neural network is to produce an output pattern when presented with an input pattern.

Traditionally the term neural network was used to refer to a network or circuit of biological neurons. But the modern usage of the term often refers to artificial neural networks, which are composed of artificial neurons or nodes. Biological neural networks are made up of real human neurons that are connected or functionally related in a nervous system (see Fig. 1). In a typical ANN, input units store the inputs, hidden units transform the inputs into an internal numeric vector and an output unit transforms the hidden values into the prediction. From a practical point of view, an ANN is just a parallel computational system consisting of many simple processing

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elements like units, connections and weights with numeric inputs and out- puts connected together in a specific way in order to perform a particular task. A simple artificial neural network model with multi-input and single-output is presented in Fig. 2. Basic components of artificial neurons are described as follows:

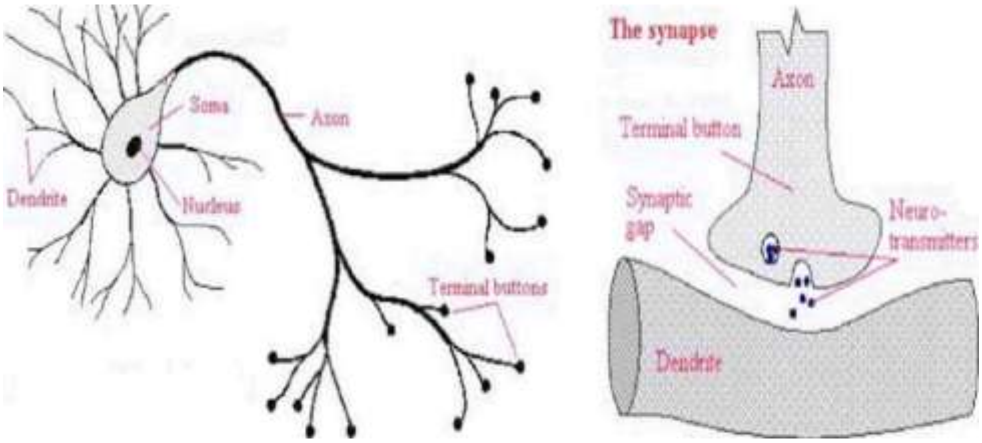

Fig. 1: Schematic diagram of biological neuron

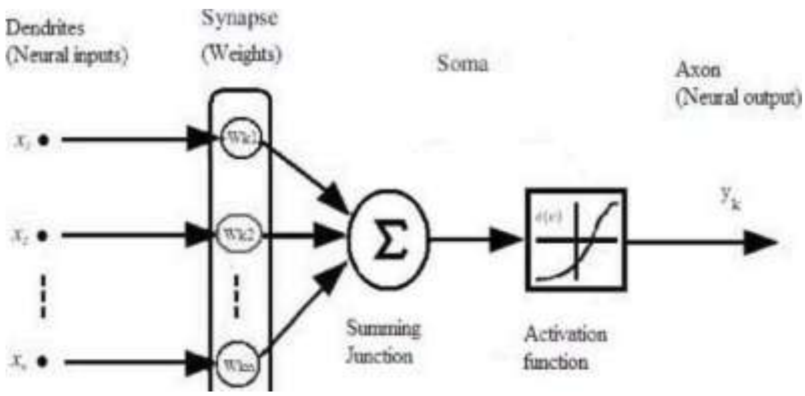

Fig. 2: A simple model of artificial neural network

∗ A set of connections (that is, synapses) brings in activations from other input neurons (dendrites) and provides long-term memory to the past accumulated experience.

∗ A processing unit (soma) sums the inputs and then applies a non-linear activation function (that is, transfer/threshold function); almost all the logical functions of the neuron are carried out in the soma.

∗ An output line (axon) transmits the result to other neurons.

ANNs processes the information using connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. The typical elements of an artificial neural network are generally described as the network architecture, learning algorithm and activation function.

5. CONCLUSION

This systematic literature review has comprehensively examined recent developments in the field of image reconstruction and de-noising using neural network-based approaches. The analysis of research articles reveals that deep learning techniques, particularly Convolutional Neural Networks (CNNs), Autoencoders, Generative Adversarial Networks (GANs), and Recurrent Neural Networks (RNNs), have significantly advanced the state-of-the-art in image restoration tasks. CNNs remain dominant due to their strong feature extraction capabilities, while GANs have proven effective in producing perceptually high-quality images. Autoencoders offer simplicity and efficiency, especially in unsupervised learning scenarios, and RNNs bring value to temporal de-noising in video sequences.

Despite notable progress, several challenges persist. These include the limited generalization of models to unseen noise types, lack of interpretability in deep models, high computational cost, and difficulties in training complex architectures like GANs. Moreover, deploying such models in real-time, resource-constrained environments remains a key concern.

The review also identifies promising directions for future research, such as the integration of hybrid neural models, self-supervised and federated learning approaches, and physics-informed deep learning. These emerging strategies have the potential to enhance model robustness, scalability, and adaptability.

In conclusion, neural network-based image reconstruction and de-noising have demonstrated remarkable potential, offering solutions that significantly outperform traditional methods. However, to move towards more reliable, interpretable, and deployable systems, further exploration into model optimization, generalization, and application-specific customization is essential. This review serves as a foundational reference for researchers aiming to contribute to this dynamic and impactful domain.

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