# An Efficient Denoising of Medical Images Through Convolutional Neural Network

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**Abstract.** Denoising medical images is a critical step in enhancing image quality and improving diagnostic accuracy. In this work, an efficient denoising method has been proposed for medical images using convolutional denoising autoencoders. The proposed approach leverages the power of CNNs to learn complex patterns and features from a large dataset of clean and noisy medical images. To train the denoising network, a dataset has created consisting of pairs of clean medical images and their corresponding noisy versions. Various types and levels of noise are introduced to generate a diverse training set. The network architecture is carefully designed to effectively capture and extract relevant features from the noisy medical images. Multiple convolutional layers are used for feature extraction, followed by pooling, normalization, and non-linear activation layers. The final layers of the network focus on reconstructing the clean version of the input image. During the training phase, the network learns to map the noisy images to their corresponding clean versions. A suitable loss function, such as mean squared error or structural similarity index loss, is employed to guide the training process, and minimize the discrepancy between the network output and the ground truth clean image. The trained network is evaluated on a separate test dataset, and performance metrics such as peak signal-to-noise ratio and visual inspection are used to assess the denoising effectiveness. The experimental results demonstrate that the proposed CNN-based denoising method achieves superior performance compared to traditional denoising techniques. The network effectively reduces noise artifacts while preserving important image details and structures. The denoised medical images generated by the CNN can potentially lead to improved diagnosis and decision-making in medical applications.

**Keywords:** Medical image denoising · Convolutional denoising autoencoders · Deep learning · Image reconstruction · Quantitative evaluation · Visual inspection · Diagnostic accuracy


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## 1 Introduction

Denoising medical images using Convolutional Neural Networks (CNNs) is an effective approach to enhance image quality and remove noise artifacts. CNNs have demonstrated remarkable performance in various image processing tasks, including medical image denoising. The denoising of medical images have certain phases include: data preparation; dataset augmentation; architecture; training; optimization; evaluation; and post pre-processing. The success of the denoising process relies on the quality and diversity of the training dataset, as well as the design of the network architecture and the hyperparameter settings. Iterative refinement, cross-validation, and assembling techniques can be employed to improve performance further [1]. Additionally, various advanced techniques have been developed to address specific challenges in medical image denoising, such as incorporating attention mechanisms, using generative adversarial networks (GANs), or leveraging self-supervised learning. These techniques can provide further improvements in denoising accuracy and efficiency. Furthermore, denoising medical images is a crucial task to improve the quality and diagnostic accuracy of medical imaging. Medical images often suffer from various types of noise, including Gaussian noise, Poisson noise, motion artifacts, and electronic noise. Several denoising techniques can be applied to medical images such as: filtering techniques; wavelet-Based techniques; non-local means (NLM) denoising; deep learning-based techniques; patch-based techniques [2].

These are some of the commonly used techniques for denoising medical images. The choice of method depends on the specific characteristics of the noise, the desired level of denoising, and the trade-off between noise reduction and preservation of important image features. It is important to evaluate the denoising results using appropriate metrics and, when necessary, involve medical experts to assess the impact on diagnosis and clinical decision-making. However, these techniques need large computational time and huge data set requirements in order to achieve better performance [3]. Hence, in tis work the denoising of medical images has been done based on Convolutional denoising autoencoders (CDAEs). These are a specific type of denoising autoencoder that leverage convolutional neural network (CNN) architectures for denoising tasks, particularly in image denoising applications. CDAEs follow the same basic principles as traditional autoencoders but incorporate convolutional layers in the encoder and decoder components. These convolutional layers allow the model to efficiently capture spatial features and patterns present in the input images. During the training process, a dataset of clean images is corrupted by introducing noise, such as Gaussian noise or random pixel perturbations, to generate the corresponding noisy images [4].

The CDAE is trained to encode the noisy images into a lower-dimensional representation and reconstruct the clean images using the decoder component. The loss function used during training typically measures the discrepancy between the reconstructed clean images and the original clean images. This encourages the CDAE to learn meaningful representations and effectively remove noise during the reconstruction process. The convolutional layers in CDAEs enable the models to capture local patterns and features in the input images, making them particularly suitable for denoising tasks where preserving spatial information is crucial. The hierarchical nature of CNNs allows for the extraction of complex and abstract image features, aiding in noise suppression while retaining important image details. Once trained, CDAEs can be applied to denoise new, unseen noisy images by passing them through the encoder to obtain the compressed representation and then using the decoder to reconstruct the denoised versions. Convolutional denoising autoencoders have demonstrated effectiveness in various domains, including medical image denoising [5, 6]. They have the potential to improve the quality of medical images, enhance diagnostic accuracy, and support medical professionals in making informed decisions. Finally, convolutional denoising autoencoders provide a powerful framework for effectively denoising images, leveraging the benefits of convolutional neural networks to handle spatially structured data, such as medical images, and removing noise while preserving important image features.

## 2 Literature Review

Medical image processing has recently attracted a lot of attention from researchers who are trying to diagnose and cure dangerous illnesses like cancer. Medical image analysis is thought to depend heavily on the process of denoising of images. Image denoising constitutes a fundamental undertaking within the realm of image processing. Its primary objective is to effectively eliminate undesired noise from an image, all the while safeguarding and retaining crucial details present in the visual content. This can effectively accomplish using a variety of Deep Learning approaches, such as autoencoders. A convolutional autoencoders-based method for medical picture denoising with short connections has been suggested in [7], which uses three datasets of medical imaging data for denoising. The outcomes showed that, across all three datasets, the suggested methodology outperformed the most advanced medical picture denoising techniques currently available. The authors of [8] has created a denoising convolutional autoencoder that first creates an encoded, lower-dimensional representation of the picture before recovering the original image from the lower-dimensional representation. By introducing random noise, the denoising autoencoders create corrupted copies of the input pictures and try to remove the noise from the noisy input to recreate an output that is very close to the original input. To compress and denoise grayscale medical pictures, a 3-layer autoencoder model has been suggested in [9].

A deep learning approach, to the denoising issue has been analyzed in [10]. The proposed algorithm eliminates unwelcome noise from a picture, autoencoders employ down- and up-sampling algorithms. The authors of [11], has investigated CNN architecture for sophisticated image denoising. A clustering technique for effective denoising of medical images based on CNN has been suggested by the authors in [12]. Convolutional neural networks (CNNs) are proposed [13] for the prediction of Parkinson's

Disease utilizing an autoencoder feature extraction approach. An autoencoder is used to extract features from input data and de-noise it. For categorization and forecasting, CNN is employed. The goal of image enhancement is to create a clear image from a noisy image, and ultrasound images are one application. In contrast to traditional picture enhancing techniques, deep learning was employed in the experimental investigation [14]. The convolutional denoising autoencoder network, one of the deep learning techniques, was used to attempt to eliminate various amounts of speckle noise that had been introduced to ultrasound pictures of the brachial plexus, also known as the big nerve community under the armpit. A significant number of noise sources significantly pollute extracellular recordings, making the denoising procedure a very difficult work that must be taken on for effective spike sorting. In order to do this, the authors of [15] suggested an end-to-end deep learning solution using a fully convolutional de-noising autoencoder, which learns to create a clear neural activity signal from a noisy multichannel input.

Using receiver operator characteristic (ROC) approaches, the authors of [16] suggested a task-based evaluation of reduced dosage reconstruction and denoising procedures. For the LDCT denoising challenge, the authors of [17] has suggested a brand-new 3D self-attention convolutional neural network. To train a domain-specific autoencoder as the perceptual loss function, the same authors also provide a self-supervised learning strategy. The authors of [18] has combined two approaches and use extensive experiments to show their efficacy on neural networks built using WGAN and CNN, respectively. A novel hybrid image compression-encryption scheme, has been introduced in [19] that leverages deep learning techniques, specifically stacked auto-encoders, in conjunction with the logistic map. The advanced encryption standard (AES) and data encryption standard (DES) are used to encrypt the DCT-based compression algorithm presented in [20]. In order to ensure safe data transfer, the biorthogonal discrete wavelet transform (DWT) approach is introduced in [21] for compression, followed by the advanced encryption standard (AES) and data encryption standard (DES) technologies. The unnecessary data is suggested to be removed using the fractal-based compression algorithm [22] because it does not depend on the image resolution. The grayscale images in [23] are compressed using the Huffman lossless compression technique. In addition, several algorithms have been proposed for encryption [24], encryption [25, 26], haze removal based on DCP [27], DWT [28], and feed forward ANN [29] and security [30, 31].

The literature review highlights the effectiveness of CDAEs in medical image denoising and their potential for further advancements. It emphasizes the importance of denoising for improving image quality and aiding in accurate diagnosis in medical imaging applications. Hence, this work focuses on medical image denoising based on CNN auto encoders for variety of noise sources. The performance measures have been estimated for different noise variance in terms of SSIM and PSNR.

## 3 Methodology

### 3.1 Autoencoders.

Autoencoders are a type of artificial neural network that is primarily used for unsupervised learning tasks such as data compression, feature extraction, and reconstruction. The basic autoencoder architecture consists of an encoder and a decoder, which work together to learn a compressed representation of the input data and reconstruct it as closely as possible. Given a collection of unlabeled training inputs ($x^1$, $x^2$, $x^3$.....,$x^n$), which is represented using (Eqs. (1). It initially employs deterministic mapping using (Eqs. (2) via sending an input, where any nonlinear function, s, may be used [32].

$$z^{(i)} = x^{(i)}, i = 1\, to\, n \tag{1}$$

$$y = s(Wx + b) \tag{2}$$

The encoder takes an input data sample and maps it to a lower-dimensional representation or code. The encoder network typically consists of multiple layers, such as fully connected layers or convolutional layers, that progressively reduce the dimensionality of the input. Each layer of the encoder learns to extract increasingly abstract features from the input data. The basic architecture of convolutional architecture has depicted in Fig. 1, where, layer L1 serves as the input layer. Layer L2 uses latent representation to encode layer L1, while layer L3 reconstructs layer L1.

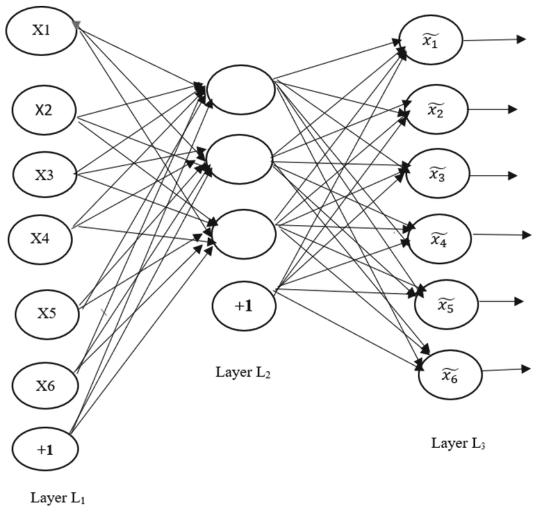


**Fig. 1.** Architecture of a basic autoencoder.

### 3.2 Denoising Autoencoders

Denoising autoencoders are a type of autoencoder specifically designed to remove noise or artifacts from input data. They are trained on corrupted data samples and learn to reconstruct the original, clean data by capturing the underlying structure and removing the noise components. Denoising autoencoders have been widely used in various domains, including image denoising, speech denoising, and signal denoising. Denoising autoencoders take corrupted or noisy input data as their input. The corruption process can involve adding random noise, introducing occlusions, or applying other forms of data corruption. The encoder network in a denoising autoencoder processes the corrupted input and maps it to a latent or compressed representation. The encoder learns to extract meaningful features from the noisy input, while filtering out the noise components. The decoder network reconstructs the clean data from the compressed representation obtained from the encoder. The decoder aims to generate output that closely resembles the original, noise-free input. Denoising autoencoders provide an effective approach for removing noise from corrupted data [32, 33]. They learn to reconstruct the original, clean data by capturing the underlying structure and filtering out the noise components. By training on corrupted data, denoising autoencoders can enhance the quality and utility of data in various domains. The basic architecture of denoising autoencoders are represented in Fig. 2.

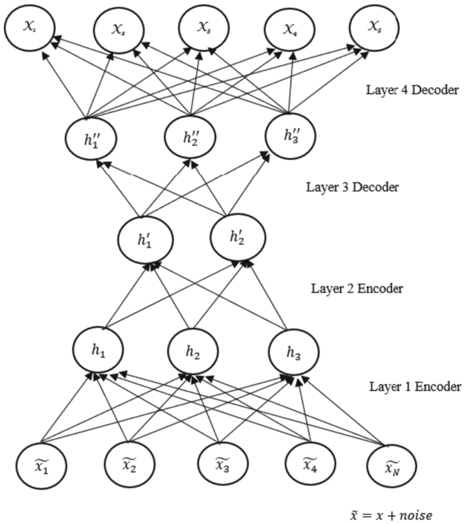


**Fig. 2.** Architecture of a denoising autoencoder.

### 3.3 Convolutional Autoencoders

Convolutional autoencoders are a type of autoencoder architecture that utilizes convolutional neural networks (CNNs) as both the encoder and decoder components. They are specifically designed for processing and reconstructing high-dimensional data, such as images, while preserving spatial information and capturing local features. Weights are distributed among all input regions in convolutional autoencoders, preserving local spatiality. The $i^{th}$ feature map's representation is provided in (Eqs. (3).

$$h^i = s(x * W^i + b^i) \tag{3}$$

where * stands for convolution (2D), s is an activation, and bias is broadcast to the whole map. Utilizing a single bias per latent map, reconstruction yields which is represented using (Eqs. (4). If W is a flip operation across both weight dimensions, H is a collection of latent feature maps, and c is bias per input channel.

$$y = s\left(\sum_{i \in H} h^i * W^i + c\right) \tag{4}$$

### 3.4 Data Set

A data set consisting 731 images with 512x420 resolution of X-ray images of human body parts. Some of the random images from dataset has depicted in Fig. 3.

Instead, adding noise to one image at a time, a flattened dataset has been corrupted, each row representing each image, so disrupting all photos at once. Datasets that have been corrupted were then utilized for modelling. Convolutional denoising autoencoder (CNN DAE), seen in Fig. 4, has been built using a rather straightforward design [31].

## 4 Simulation Results

### 4.1 Subjective Analysis

Subjective analysis in image processing refers to the evaluation and interpretation of images based on human perception and judgment. For the random images taken from dataset, the subjective analysis has been done which is depicted in Fig. 5 for gaussian noise with different noise proportions (*np*).

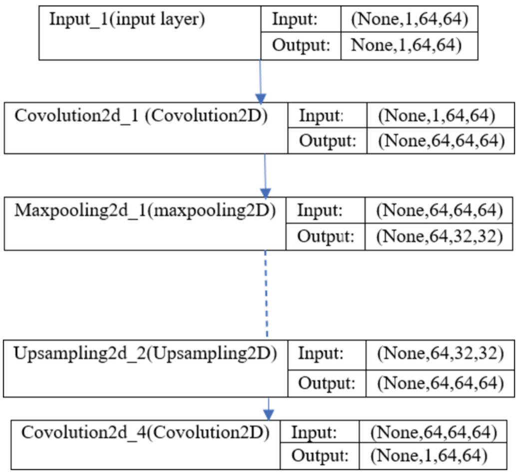


**Fig. 4.** Architecture of CNN DAE.

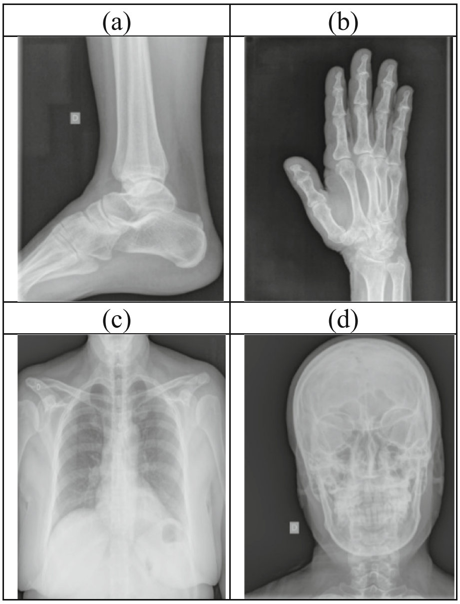


**Fig. 3.** Random samples of medical x-ray images from the dataset.

## 4.2 Objective Analysis

Objective analysis in image processing refers to the quantitative assessment and measurement of various characteristics, properties, and metrics of an image. The proposed methodology has undergone an objective analysis in terms of PSNR, MSE, under various noise (Gaussian and Poisson) patterns. SSIM has been analyzed using the Eqs. (5), where *l, c, s* are brightness, disparity and basic components which are calculated using Eqs. (6), (7), and (8) respectively. Where $\mu_x$ and $\mu_y$ stand for the mean of the original and coded pictures, $\sigma_x$ and $\sigma_y$ for their standard deviations, and $\sigma_{xy}$ for their covariance.

$$SSIM\,(x, y) = \left[l(x, y)^{\alpha}\right]\left[c(x, y)^{\beta}\right][s(x, y)^{\gamma}] \tag{5}$$

$$l(x, y) = \frac{2\mu_x\mu_{y+C_1}}{\mu_x^2 + \mu_{y+}^2 C_1} \tag{6}$$

$$c(x, y) = \frac{2\sigma_x\sigma_{y+C_2}}{\sigma_x^2 + \sigma_{y+}^2 C_2} \tag{7}$$

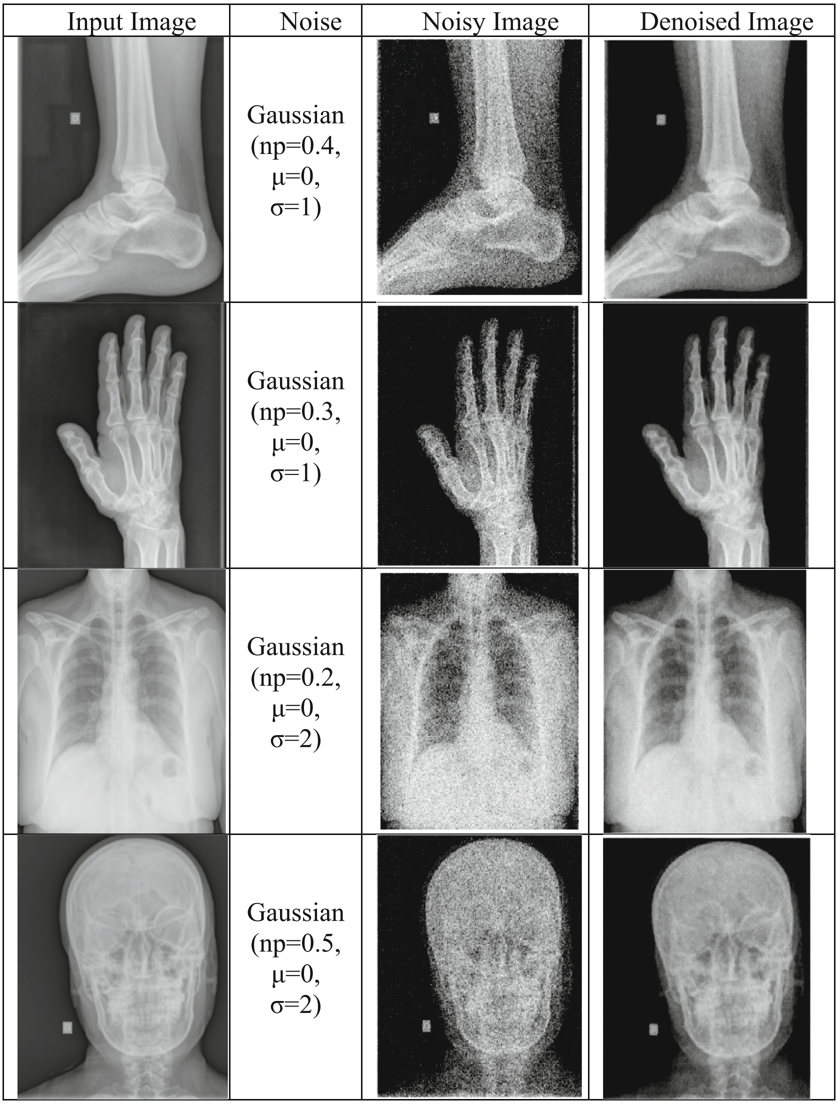


**Fig. 5.** CNN DAE's denoising performance with various Gaussian noise patterns.

$$s(x, y) = \frac{2\sigma_{xy} + C_3}{\sigma_x \sigma_y + C_3} \tag{8}$$

The detailed analysis of performance measure for CNN DAE under various noise sources has been summarized in Table 1

**Table 1.** Comparison of SSIM values for CNN DAE and median filter under various noise parameters

| Image | Noise Type | Noise Parameters | SSIM | |
|---|---|---|---|---|
| | | | Filtering | CNN DAE |
| Ankle X-ray | Gaussian | $np = 0.3, \mu = 0, \sigma = 1$ | 0.3156 | 0.8543 |
| | | $np = 0.5, \mu = 0, \sigma = 1$ | 0.2367 | 0.8478 |
| Chest X-ray | Gaussian | $np = 0.2, \mu = 0, \sigma = 2$ | 0.1762 | 0.7643 |
| | | $np = 0.1, \mu = 0, \sigma = 2$ | 0.1934 | 0.7456 |
| Skull X-ray | Poisson | $np = 0.2, \lambda = 1$ | 0.2467 | 0.4678 |
| | | $np = 0.4, \lambda = 2$ | 0.1219 | 0.5647 |
| Hand X-ray | Poisson | $np = 0.1, \lambda = 1$ | 0.1565 | 0.4878 |
| | | $np = 0.5, \lambda = 5$ | 0.1725 | 0.70 |

## 5 Conclusion

In this work a denoising autoencoder has been erected through the convolutional layers for the purpose of serving efficient denoising of medical images. A dataset of having 731 medical X-ray images have been trained and introducing various noise types such as Gaussian and Poisson, by altering various noise parameters. The simulation results depict that, the proposed CNN DAE achieves high accuracy when compared to conventional denoising approaches based on filtering. The image quality has been improved by 60% after denoising based on CNN DAE, where as 19% of accuracy has been obtained using median filtering techniques. Overall, the performance of proposed CNN DAE has attained 50% improvement in image visual accuracy when compared to conventional filtering-based image denoising techniques.

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