# Advanced Denoising Techniques for Enhanced Medical Imaging

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## 7. ABSTRACT.

This study focuses on reducing noise in medical imaging, specifically X-ray images, using advanced filtering algorithms. It applies Wiener, Non-Local Means (NLM), Total Variation (TV), and Convolutional Autoencoders (CAE) to enhance image quality and preserve important features for accurate diagnosis. The study investigates the impact of Poisson and Gaussian noise on chest X-rays and compares the performance of CAE with the traditional Wiener filter (WF). Using metrics like Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR), results show that CAE effectively reduces noise, demonstrating its potential for clinical applications.

**Keywords:**Convolutional Autoencoder, Wiener filter, Non-Local Means, Total Variation.

## 1. INTRODUCTION

Medical imaging plays a crucial role in healthcare for diagnosis, treatment planning, and monitoring. However, noise in images, caused by factors like faulty equipment, background interference, or patient movement, can obscure valuable information and reduce image clarity, leading to inaccurate diagnoses. Traditional noise reduction methods like NLM and TV often fail to preserve fine details in images. Convolutional Autoencoders (CAEs), a deep learning approach, offer a solution by learning patterns in noise and reducing it without losing important information. Combining CAEs with traditional filters can enhance the quality of X-ray images, making them more reliable for clinical use.

## 2. LITERATURE REVIEW

Medical imaging is vital for diagnosis and treatment, but noise from equipment, interference, or patient movement can obscure key information, leading to inaccurate diagnoses. Traditional noise reduction methods like NLM and TV often fail to preserve fine details. Convolutional Autoencoders (CAEs), a deep learning technique, help reduce noise while retaining important image features. Combining CAEs with traditional filters improves X-ray image quality, enhancing their reliability for clinical use.

## 3. METHODLOGY

The JSRT (Japanese Society of Radiological Technology) dataset [1] is used in this study as the initial source of X-ray images. This dataset is widely used in medical image processing researchproviding high-quality, annotated chest X-ray images. It includes both normal and abnormal images, offering a valuable base for developing and testing noise filtering techniquesaimed at enhancing image quality for clinical applications.

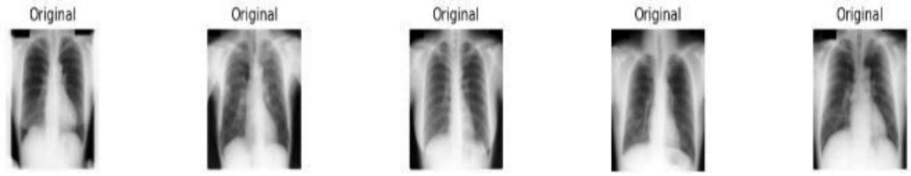


**Figure 3.1. shows that the sample images from the JSRT dataset [1] and noise will be added to that the original images.**

### 3.1 *Convolutional Autoencoders (CAE)*

Convolutional Autoencoders (CAEs) automatically learn and extract features from data, making them ideal for complex noise reduction. Using convolutional layers, CAEs capture spatial hierarchies and efficiently remove noise while preserving important details. Their ability to automatically extract features and learn deep representations allows them to handle various noise types without the need for manual feature design.

$$MSE = \frac{1}{s}\sum_{j=1}^{s}(f\,(\,,\theta) - f\,)^2 \qquad (3.1)$$

### 3.2 *Wiener filter (WF)*

The Wiener filter is designed to remove Gaussian noise, making it ideal for medical images affected by random noise from equipment or the environment. It adjusts filtering based on local mean and variance, balancing image sharpness and noise reduction. Its adaptive filtering effectively eliminates noise while preserving fine details, ensuring accurate medical interpretation.

### 3.3 *Non-Local Means (NLM) filter*

The NLM filter removes structured noise by leveraging the self-similarity of pixel neighborhoods across an image. It searches for similar regions and averages them to eliminate noise. This technique is particularly effective in medical images with repetitive structures, as it removes noise without blurring edges or erasing important features, which is crucial for accurate medical diagnosis

### 3.4 *Implementation*

The project implementation involves several stages to enhance model performance and ensure effective noise reduction in X-ray images. Key steps include data preparation, CAE model design, applying traditional filters, and training and testing procedures.

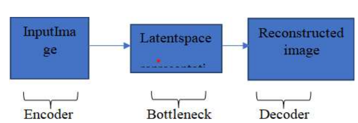


Figure 3.2 simple block diagram of a CAE

## 4. RESULTS AND DISCUSSION

### 4.1 *Quantitative Analysis*

Performance was assessed using Accuracy, which measures the system's ability to remove noise while preserving image details, and the $R^2$ score, reflecting how closely denoised images match the original clean images. The hybrid approach combining CAE with traditional filters outperformed standalone methods in both metrics, achieving superior noise reduction with minimal loss of important features**.**

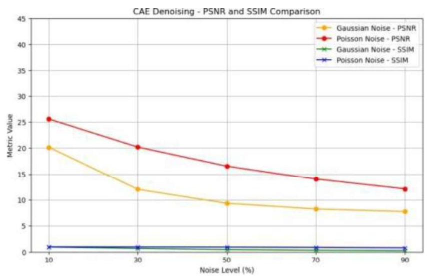


**Figure 4.1. PSNR & SSIM (CAE)**

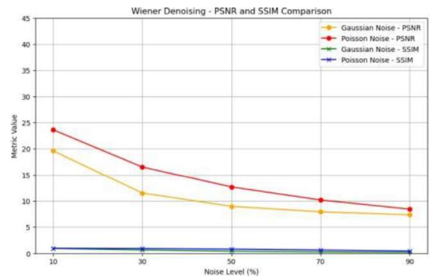


**Figure 4.2. PSNR & SSIM(Wiener)**

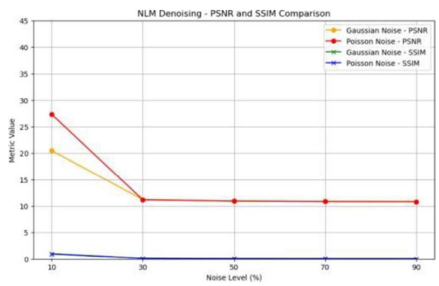


**Figure 4.3. PSNR & SSIM(NLM)**

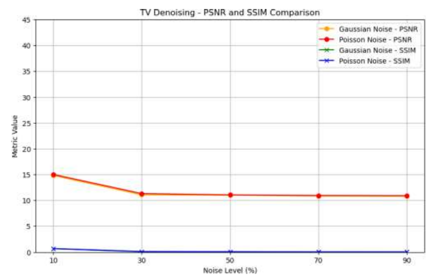


**Figure 4.4. PSNR & SSIM(TV)**

Figure 4.3 shows that the PSNR & SSIM comparison of wienervalues using different noises at various percentages.

Figure 4.4 shows that the PSNR & SSIM comparison of NLM Denoising technology at various percentages.

Fig.6. Shows that the PSNR & SSIM comparison of TV Denoising technique at variouspercentages.

### 4.2 *Visual and Metric Comparisons*

Table I summarizes the performance of each technique. Thecombination of CAE with the Wiener filter yielded the highest accuracyand R² score, suggesting it is the most effective setup for X-ray denoising in this context. Visual inspections of the enhanced images confirm reduced distortions and improved sharpness, which is critical for medical diagnostics

Table II shows the PSNR values given by wiener, NLM, TV and CAE techniques are used for Comparison of Denoising Techniques on Gaussian noise.

| Technique | Accuracy | $R^2$ Score |
|---|---|---|
| CAE | 95.25% | 0.9909 |
| NLM | 92.38% | 0.9885 |
| Wiener | 80.69% | 0.9772 |
| TV | 94.16% | 0.9902 |

**TABLE I. COMPARISON OF DENOISING TECHNIQUES ON JSRT ON GAUSSIAN NOISE**

| Gaussian noise | 10% | 30% | 50% | 70% | 90% | Average |
|---|---|---|---|---|---|---|
| Wiener | 19.62 | 11.52 | 8.96 | 7.93 | 7.36 | 11.076 |
| NLM | 20.48 | 11.21 | 10.91 | 10.85 | 10.81 | 12.855 |
| TV | 14.77 | 11.05 | 11.00 | 10.83 | 10.78 | 11.686 |
| CAE | 20.18 | 12.00 | 9.33 | 8.24 | 7.73 | 11.498 |

**TABLE II. PSNR COMPARISON OF DENOISING TECHNIQUES**

Table III shows the PSNR values given by wiener, NLM,TV and CAE techniques are used for Comparison of Denoising Techniques on Poisson noise. While CAE achieves at an average Poisson Noise of 17.677.

Table IV shows that the SSIM Comparison of Denoising Techniques on Gaussian noise between these techniques While CAE achieves at an average 0.529.

| Poisson Noise | 10% | 30% | 50% | 70% | 90% | Average |
|---|---|---|---|---|---|---|
| Wiener | 23.64 | 16.53 | 12.67 | 10.19 | 8.44 | 14.295 |
| NLM | 27.35 | 11.18 | 10.94 | 10.86 | 10.83 | 14.233 |
| TV | 14.97 | 11.32 | 11.03 | 10.93 | 10.89 | 11.824 |
| CAE | 25.59 | 20.19 | 16.53 | 13.98 | 12.10 | 17.677 |

**TABLE III: PSNR COMPARISON OF DENOISING TECHNIQUES ON POISSON NOISE**

| Gaussian Noise | 10% | 30% | 50% | 70% | 90% | Average |
|---|---|---|---|---|---|---|
| Wiener | 0.943 | 0.657 | 0.421 | 0.284 | 0.196 | 0.500 |
| NLM | 0.947 | 0.106 | 0.040 | 0.028 | 0.018 | 0.228 |
| TV | 0.665 | 0.068 | 0.093 | 0.035 | 0.022 | 0.177 |
| CAE | 0.946 | 0.679 | 0.455 | 0.323 | 0.244 | 0.529 |

**TABLE IV: SSIM COMPARISON OF DENOISING TECHNIQUES ON GAUSSIAN NOISE**

Table V shows that the SSIM Comparison of Denoising Techniques on Gaussian noise between these techniques While CAE achieves at an average Poisson noise of 0.909

| Poisson noise | 10% | 30% | 50% | 70% | 90% | Average |
|---|---|---|---|---|---|---|
| Wiener | 0.983 | 0.931 | 0.817 | 0.647 | 0.449 | 0.765 |
| NLM | 0.989 | 0.095 | 0.043 | 0.024 | 0.018 | 0.234 |
| TV | 0.674 | 0.120 | 0.055 | 0.032 | 0.024 | 0.181 |
| CAE | 0.987 | 0.969 | 0.931 | 0.870 | 0.786 | 0.909 |

**TABLE V: SSIM COMPARISON OF DENOISING TECHNIQUES ON POISSON NOISE**

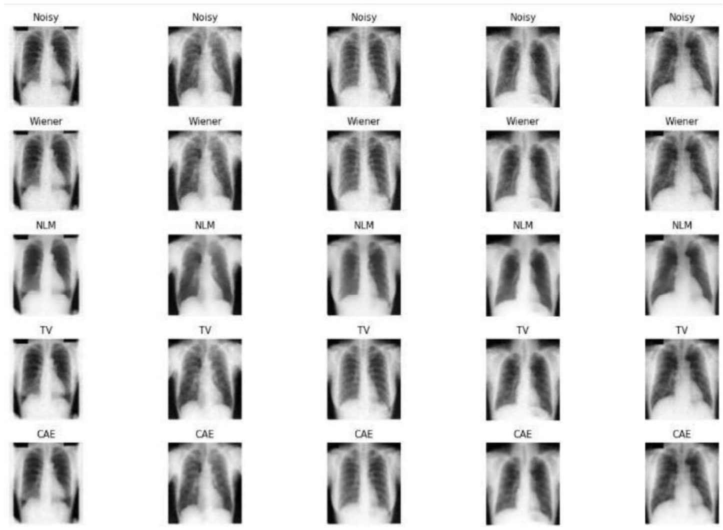


**Figure 4.1 Visualization Results**

Fig.7. show that the overall results of the hybrid CAE approach significantly improve the noise reduction in medical imaging, facilitating clearer and more accurate image interpretations.

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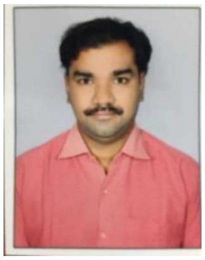

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