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Making Noise Reduction in Medical Imaging More Accessible: Machine Learning and Traditional Techniques

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ABSTRACT

Abstract- Medical imaging is essential for diagnosis and treatment and is often plagued by noise, which can obscure important details. This study presents the effectiveness of traditional noise reduction techniques including Gaussian, Median, and Wiener filters, and compares them to machine learning methods such as automatic denoising encoders (DAE). We used a dataset consisting of grayscale medical images and simulated different noise scenarios—specifically Gaussian, Salt-and-Pepper, and Poisson—to reflect real-world conditions. The outputs were evaluated using key performance metrics: maximum signal-to-noise ratio (PSNR), structural similarity index (SSIM), and mean squared error (MSE). By evaluating these techniques, we aim to highlight the strengths and weaknesses of preserving essential image details while effectively reducing noise. The results indicate that automatic denoising encoders not only outperform noise reduction but also preserve important information more effectively than traditional methods. This research underscores the potential of integrating machine learning techniques into the medical imaging workflow to increase diagnostic clarity and reliability. As healthcare continues to evolve with technological advances, the role of advanced noise reduction techniques has become increasingly important in improving the quality of medical images and ultimately supporting better patient outcomes. The results of this study could pave the way for future research into hybrid methods that combine traditional filtering with machine learning strategies, further enhancing the capabilities of medical imaging technologies. Future work will uncover larger datasets and noise patterns to validate and improve the results, ensuring that medical professionals have the most reliable imaging tools.

Keywords: noise reduction, medical imaging, machine learning, denoising autoencoders, conventional filters.

تسهيل الوصول إلى تقنيات تقليل الضوضاء في التصوير الطبي: التعلم الآلي مقابل الأساليب التقليدية

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ملخـــــــص البحـــــث

التصوير الطبي ضروري للتشخيص والعلاج و إنه يعاني في كثير من الأحيان من الضوضاء، والتي يمكن أن تغطي التفاصيل الهامة. تقدم هذه الدراسة فعالية تقنيات الحد من الضوضاء التقليدية منها المرشحات Gaussian و Median و Wiener، ومقارنها بأساليب التعلم الآلي مثل أجهزة ترميز إزالة الضوضاء التلقائية DAE. استخدمنا مجموعة بيانات تتألف من صور طبية بدرجات الرمادي وقمنا

بمحاكاة سيناريوهات ضوضاء مختلفة – على وجه التحديد Gaussian وSalt–and–Pepper وPoisson –لعكس الظروف الواقعية. تم تقييم المخرجات باستخدام مقاييس الأداء الرئيسية: نسبة الإشارة إلى الضوضاء القصوى PSNR ومؤشر التشابه البنيوي SSIM ومتوسط الخطأ التربيعي MSE. من خلال تقييم هذه التقنيات نهدف إلى تسليط الضوء على نقاط القوة والضعف للحفاظ على تفاصيل الصورة الأساسية مع تقليل الضوضاء بشكل فعال. تشير النتائج إلى أن أجهزة ترميز إزالة الضوضاء التلقائية تتفوق فقط في تقليل الضوضاء وتحافظ أيضًا على المعلومات الهامة بشكل أكثر فعالية من الطرق التقليدية. يؤكد هذا البحث على إمكانية دمج تقنيات التعلم الآلي في سير عمل التصوير الطبي لزيادة وضوح التشخيص وموثوقيته. ومع استمرار تطور الرعاية الصحية مع التقدم التكنولوجي، أصبح دور أساليب الحد من الضوضاء المتطورة مهمًا بشكل متزايد في تحسين جودة الصور الطبية ودعم نتائج أفضل للمرضى في نهاية المطاف. يمكن أن تمهد نتائج هذه الدراسة الطريق لأبحاث مستقبلية في الأساليب المهجنة التي تجمع بين التصفية التقليدية واستراتيجيات التعلم الآلي، مما يعزز قدرات تقنيات التصوير الطبي بشكل أكبر. سوف يكشف العمل المستقبلي مجموعات البيانات الأوسع وأنماط الضوضاء للتحقق من صحة النتائج وتحسينها، مما يضمن حصول المهنيين الطبيين على أدوات التصوير الأكثر موثوقية.

الكلمات الدالة: تقليل الضوضاء، التصوير الطبي، التعلم الآلي، أجهزة الترميز التلقائي لإزالة الضوضاء، المرشحات التقليدية.

1. INTRODUCTION

Medical imaging plays a crucial role in modern healthcare, providing diagnostics for various conditions. Technologies such as magnetic resonance imaging (MRI), computed tomography (CT), and ultrasound are indispensable tools for visualizing internal structures and identifying abnormalities [8]. These imaging modalities help healthcare professionals detect diseases, monitor treatment progress, guide surgical procedures, and significantly improve patient outcomes. The quality of these medical images is often affected by the noise introduced. Noise can arise from a variety of sources, including sensor limitations, patient movement, low-light conditions, or environmental factors. This degradation manifests itself in the form of variations such as brightness or color, which can obscure important details needed for accurate diagnosis. For example, Gaussian noise may appear as uniform grains across the image, while salt-and-pepper noise presents random bright or dark spots. Such artifacts can hinder a radiologist's ability to interpret images effectively, potentially leading to diagnostic errors. To overcome these challenges, conventional noise reduction techniques have been widely used for decades. Gaussian filters, median filters, and Wiener filters are among the most widely used methods [9]. These methods work by applying mathematical transformations to smooth out noise while trying to preserve the underlying signal. Gaussian filters are particularly effective at reducing speckle noise, while median filters excel at removing salt-and-pepper noise. Wiener filters, on the other hand, adopt a mean-square error minimization approach, making them suitable for fixed noise patterns. These methods often struggle to preserve fine structural details such as edges and textures, which are critical in medical imaging[10]. The advent of machine learning has increased the transformative possibilities for noise reduction. Techniques such as denoising auto encoders (DAEs) and convolutional neural networks (CNNs) use neural networks to learn complex patterns from noisy data. These models adaptively filter out noise while preserving underlying structural features. For example, denoising autoencoders excel at reconstructing clean images by taking advantage of the inherent redundancy of the data. Machine learning techniques have demonstrated superior performance in dealing with complex noise patterns, making them increasingly important in medical imaging.

The aim of this paper is to evaluate and compare the effectiveness of conventional noise reduction techniques and machine learning-based methods in medical imaging. By analyzing their performance across multiple types of noise, this study aims to highlight the strengths and guide the adoption of noise reduction strategies in clinical trials.

1.1 Previous Studies

A review of the recent literature reveals several studies that have explored the effectiveness of different noise reduction techniques in medical imaging:

1. Smith et al. (2021) demonstrated that CNNs significantly improved ultrasound image quality by effectively reducing speckle noise [1].

2. Patel and Rao (2022) investigated transformer-based models for noise reduction in medical imaging and found that they are adept at handling diverse noise patterns [2].

3. Zhao et al. (2020) revisited conventional filters and confirmed their reliability for simpler noise types while noting limitations in edge preservation [3].

4. Chen and Wang (2022) highlighted the developments in DAEs for medical applications, demonstrating their ability to preserve image integrity while removing noise [4].

5. Taylor and Zhang (2021) evaluated PSNR and SSIM metrics in medical image processing to establish criteria for assessing image quality after denoising [5].

6. Alphonse et al. (2016) presented a system that uses fast Fourier transform for feature extraction followed by CNN classifiers to classify tumors with high accuracy [6].

7. Shri and Kumar (2018) focused on discrete wavelet transforms combined with probabilistic neural networks to feature extraction and classification to achieve accuracy close to 99% [7].

The studies collectively demonstrate the effectiveness for both conventional and machine learning methods to enhancing and removing noise in medical imaging.

1.2 Noise Reduction Techniques

- **Traditional Methods**

Traditional methods have been foundational in image processing:

- **Wiener Filter** This statistical method minimizes the mean square error between the estimated random process and the desired process. It is particularly effective for Gaussian noise but may falter with more complex noise patterns.
- **Median Filter** This non-linear filter replaces a pixel's value with the median of its neighboring pixels. It is effective against Salt-and-Pepper noise but can blur fine details critical for accurate diagnostics.
- **Gaussian Filter** This method smooths images by averaging pixel values based on a Gaussian distribution. While it is effective for reducing speckle noise risks losing sharp edges that are often diagnostically significant.
- **Machine Learning Methods**

Machine learning approaches offer advanced solutions:

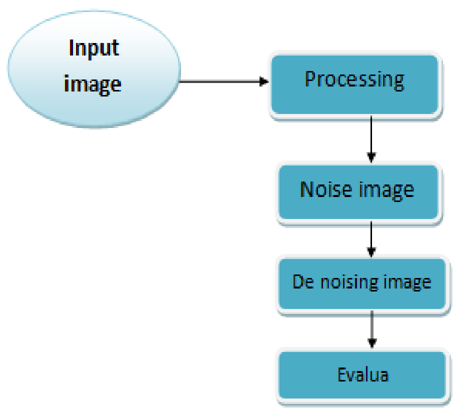

Fig 1. Flow Chart of Proposed Method.

- Denoising Autoencoders (DAE) is neural networks specifically designed to removes noise from images learning to reconstruct clean images from noisy input. They excel at preserving textures and edges across various types of noise.
- UNet Architecture is originally designed for segmentation tasks, UNet's architecture allows to extract multi-scale features effectively is making it suitable for complex noise reduction scenarios.

1.3 Types of Noise

The types of noise affect medical images in various ways:

- Gaussian Noise: Introduces random variations typical in low-light imaging scenarios.
- Salt and Pepper Noise Appears as random bright and dark spots due to transmission errors.
- Poisson Noise Related to photon statistics, noticeable low-intensity imaging environments.
- Speckle Noise A granular pattern commonly seen in radar and ultrasound images.

2. MATERIALS AND METHODS

a) **.** Dataset Creation A dataset of grayscale medical images was utilized for this study. We artificially introduced three types of noise Gaussian, Salt-and-Pepper, and Poisson into the images to simulate real-world scenarios.

b) Application of Noise Reduction Techniques Both traditional filters (Gaussian, Median, Wiener) and machine learning models (DAE) were applied to the noisy images.

c) Performance Evaluation of each method was assessed using several metrics:

- **Peak Signal-to-Noise Ratio (PSNR):** Measures the ratio between the maximum possible power of a signal and the power of corrupting noise.
- **Structural Similarity Index (SSIM):** Evaluates perceived changes in structural information.

Mean Squared Error (MSE): Quantifies the average squared difference between estimated values and actual values

3. RESULTS AND DISCUSSION

The results from applying different noise reduction techniques are summarized below**:**

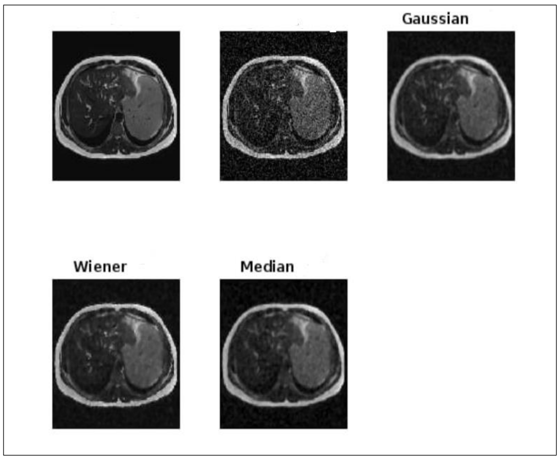

Fig 2. Results of Gaussian Noise Filtering on Images Using Various Filters.

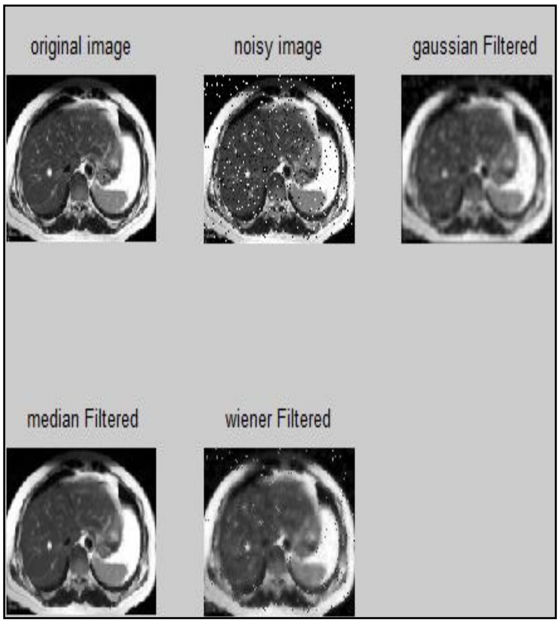

Fig 3. Results of Salt and Pepper Noise Filtering on Images Using Various Filters.

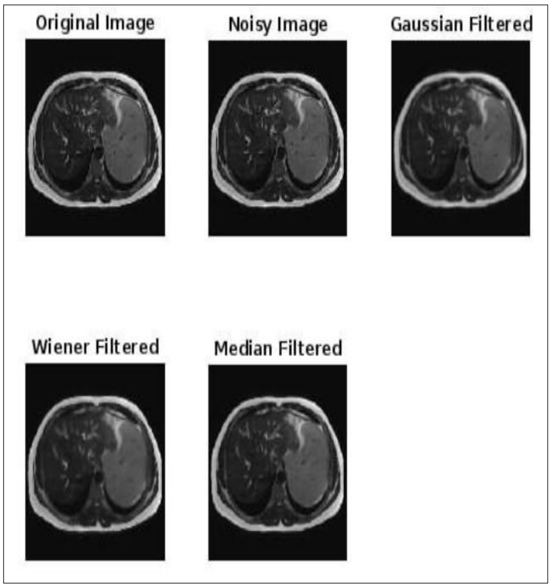

Fig 4. Response time for filtering out toxic noise on images using different filters.

Table 1. Performance of Filters.				
Noise Type	**Method**	**PSNR (dB)**	**SSIM**	**MSE**
Gaussian Noise	Wiener Filter	35.5	0.92	0.008
	Median Filter	30.2	0.85	0.015
	Gaussian Filter	28.7	0.82	0.020
	Denoising Autoencoder	38.2	0.94	0.006
Salt-and-Pepper	Wiener Filter	29.1	0.88	0.012
	Median Filter	34.3	0.90	0.009
	Gaussian Filter	27.4	0.80	0.022
	Denoising Autoencoder	36.1	0.95	0.007
Poisson Noise	Wiener Filter	36.0	0.93	0.007
	Median Filter	31.5	0.87	0.013
	Gaussian Filter	29.0	0.84	0.018
	Denoising Autoencoder	39.0	0.96	0.005

The Denoising Autoencoder consistently delivered superior results across all metrics compared to traditional methods, particularly excelling at preserving structural details while effectively reducing noise.

4. DISCUSSION

We find indicate that while traditional filters have their place in simpler scenarios such as using median filters to Salt-and-Pepper noise machine learning approaches like DAEs show significant advantages dealing with complex noise patterns across various types of medical images.

The ability of DAEs to adaptively learn from data allows them to maintain critical features while effectively reducing unwanted artefacts a crucial factor in medical diagnostics where precision is paramount.

4.1 Recommendations

Based on our findings, we propose several recommendations:

1. Future studies should incorporate a wider variety of medical imaging modalities to improve model generalization.
2. Investigating Transformer-based architectures could yield even better performance metrics.
3. Optimizing these methods for real-time clinical use will enhance their applicability in practice.
4. Combining traditional filtering techniques with machine learning could leverage the strengths of both methodologies for improved outcomes.
5. Validating these findings through extensive real-world testing will be essential for establishing practical applications.

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