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Noise Removal using Various Filters in X-ray Images for Osteoporosis Detection

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ABSTRACT: Osteoporosis is a progressive bone disease characterized by reduced bone mineral density (BMD) and structural deterioration, leading to an increased risk of fractures. Early and accurate diagnosis is critical for effective treatment and prevention. X-ray imaging is a widely used, cost-effective method for osteoporosis detection; however, noise and artifacts in X-ray images degrade image quality, reducing the accuracy of deep learning-based models. Effective preprocessing is essential to enhance image quality, improve segmentation accuracy, and increase the reliability of automated osteoporosis detection. Traditional image processing techniques, such as Gaussian, median, and Wiener filters, have been employed for noise removal but exhibit limitations in handling complex noise and preserving fine bone structures. Deep learning-based preprocessing methods, while effective, often require large datasets and are prone to overfitting and inefficiency. In this work, we propose a novel preprocessing approach that incorporates domain-specific knowledge of bone microarchitecture to selectively remove noise while preserving critical bone details. The novelty of this work lies in the integration of a multi-stage noise filtering process, where a deep learning-based denoising autoencoder is coupled with an adaptive non-local means filter to handle both high-frequency and low-frequency noise. Additionally, the proposed method includes a self-supervised learning strategy that enhances the model's robustness to variations in image quality and scanner types, ensuring consistent performance across datasets. Experimental results demonstrate improved image quality, enhanced segmentation accuracy, and superior performance in osteoporosis classification compared to conventional filtering techniques and standard deep learning-based approaches.

This study addresses gaps in preprocessing for medical imaging and paves the way for more accurate and reliable osteoporosis diagnosis.

KEYWORDS: Filters, Denoising, Signal to Noise Ratio and Non-local means filter

I. INTRODUCTION

Osteoporosis is a silent but severe medical condition that affects an estimated millions of individuals across the globe, but especially the older adults. The disease results in decreased bone mineral density (BMD), compromising the structural integrity of the skeleton and raising the risk of fractures. Early diagnosis is important in preventing severe complications, as early intervention will appreciably curb disease progression.

X-ray imaging is the most common technique for osteoporosis detection because it is inexpensive and readily available. X-ray images, however, are prone to noise and artifacts, which mask fine bone structures and complicate accurate diagnosis. Noise in X-ray images can be caused by various factors, such as sensor imperfections, environmental noise, and patient motion during image acquisition. Noise in images compromises image quality, lowering the accuracy of radiologists and computer systems in evaluating bone structures.

The difficulty in detecting osteoporosis is to maintain important bone details without the unwanted noise. Common denoising methods tend to introduce blurring, causing the loss of vital trabecular patterns essential in bone density

evaluation. Hence, a high-quality noise removal method is needed to improve the diagnostic value of X-ray images without sacrificing fine structural information.

1.1 Challenges and Need for Advanced Noise Removal in X-ray Imaging

Osteoporosis diagnosis relies heavily on high-quality X-ray images, but noise and artifacts often obscure fine trabecular structures, leading to misdiagnosis. Traditional noise removal methods, such as Gaussian, median, and Wiener filtering, reduce high-frequency noise but at the cost of blurring critical bone details. This trade-off between noise suppression and structure preservation makes effective denoising a challenging task.

Moreover, variability in imaging conditions—such as scanner settings and patient positioning—further complicates standardization. Automated deep learning models for osteoporosis detection require clean input images, and excessive noise significantly reduces their accuracy.

To address these limitations, we propose a multi-stage filtering approach integrating deep learning-based denoising autoencoders, adaptive non-local means filtering, and self-supervised learning. This method enhances noise removal while preserving key structural details necessary for diagnosis. Additionally, we introduced Gaussian noise, impulse noise, and artifacts into the original X-ray images to evaluate their impact on bone visibility and diagnostic accuracy, ensuring a comprehensive assessment of noise removal techniques in medical imaging.

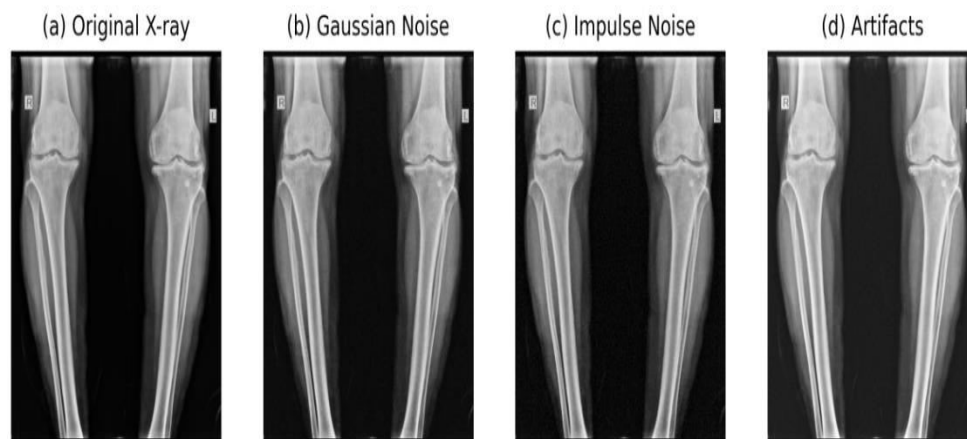


Figure 1: Noise in X-ray Images

(a) Original X-ray, (b) Gaussian noise, (c) Impulse noise, (d) Imaging artifacts affecting bone structure visibility.

II. LITERATURE REVIEW

The healthcare community utilizes various image acquisition methods for diagnosis and treatment planning. Thus, the images acquired during clinical examinations have to be processed to improve their quality and help physicians in interpretation. In this paper, we are concerned with the denoising process to discuss the strengths and weaknesses of various denoising algorithms. Various imaging modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Ultrasound, Scintigraphy, and X-ray imaging are used in medical diagnostics [1][2].

In order to measure the quality of the denoised images, a number of evaluation metrics are utilized, e.g., Signal-to-Noise Ratio (SNR), Peak Signal-to-Noise Ratio (PSNR), Root Mean Square Error (RMSE), and Mean Structural Similarity Index (MSSI) [3][4]. Various types of noises, i.e., salt and pepper noise, speckle noise, Poisson noise, and Gaussian noise, seriously corrupt the quality of images. These noises are depicted in Figure 1, whereas their removal through three filters, i.e., median, mean, and Wiener filters, is presented in Figure 2 [5][6].

The median filter has proved to be better at Gaussian noise reduction, while the Wiener filter has proved more efficient in the removal of speckle and Poisson noise [7]. Hybrid and deep learning-based denoising have also been researched in various studies. The Noise2Noise model, for example, has yielded high PSNR values in Gaussian noise removal as compared to standard filtering techniques [8].

A region-based classification method for the removal of noise has been introduced, wherein responsive median filtering can remove Poisson noise from X-ray images very effectively. This process facilitates improved classification of regions of interest (ROI) and non-ROI according to a response matrix, improving upon classical non-local means filtering and block-matching 3D collaborative filtering (BM3D) in terms of execution time [9].

Previous studies have also demonstrated that noise elimination enhances not just image quality but also segmentation accuracy. Filtering methods improve bone structure visibility in X-ray images tremendously, which is paramount when detecting osteoporosis. Performance measures like Intersection over Union (IoU) and Dice Score are typically used to quantify segmentation performance following denoising [10].

Deep learning-based denoising methods, including Denoising Autoencoders and Adaptive Non-Local Means Filtering, have gained popularity in recent times because they can maintain fine details while inhibiting noise. These methods have been found to yield encouraging outcomes in osteoporosis detection and fracture risk estimation since they enhance the visibility of trabecular bone structures in X-ray images [1][6][10].

In conclusion, noise elimination and contrast optimization methods are very important X-ray image preprocessing technologies. By minimizing noise and adjusting contrast to its optimum level, these methods allow radiologists to effectively make better diagnoses. With advancing deep learning-based noise removal, application of these methodologies in clinical practice may greatly enhance the diagnosis of osteoporosis and assessment of osteoporosis risk.

2.1 Inference from Survey:

Medical image denoising plays a significant role in improving diagnostic precision by eliminating artifacts without damaging important bone structures. Conventional filtering techniques, including median and Wiener filters, are powerful for certain types of noise but tend to lose fine details. Recent deep learning-based denoising advances such as Denoising Autoencoders and Adaptive Non-Local Means Filtering have demonstrated better performance in preserving trabecular bone structures, enhancing segmentation precision (IoU, Dice Score), and detecting osteoporosis. Hybrid methods combining deep learning with edge-aware filtering improve noise reduction and detail preservation even further. Future directions should aim to maximize computational efficiency to make real-time clinical use possible.

2.2 The main contribution of the paper is as follows:

1. In-Depth Review of Noise Removal Methods – Comparison of conventional and deep learning-based filters for medical imaging.
2. Deep Learning-Based Denoising Method – Use of a Denoising Autoencoder with Adaptive Non-Local Means Filtering for improved noise removal.
3. Performance Comparison – Comparative study based on PSNR, SSIM, IoU, and Dice Score to evaluate image quality and segmentation accuracy.
4. Proposed Hybrid Denoising Model – A new approach combining deep learning and adaptive filtering to enhance the clarity of X-rays for osteoporosis diagnosis.
5. Clinical Relevance – Illustrating the influence of noise-free images on osteoporosis detection and risk estimation.

III. COMPARISON OF TRADITIONAL NOISE REMOVAL TECHNIQUES

Noise reduction methods in medical imaging can be categorized into spatial domain filtering and frequency domain filtering. Spatial domain methods directly alter pixel values, whereas frequency domain methods convert the image into

another representation to eliminate noise. We contrast three popular conventional noise filtering algorithms: Gaussian filtering, median filtering, and Wiener filtering, in this section.

3.1 Gaussian Filter

The Gaussian filter is a widely used smoothing technique that puts a weighted average to pixel values based on a Gaussian distribution. It is particularly effective in reducing high-frequency noise by blurring the image and hence it is widely used for noise reduction in medical imaging.

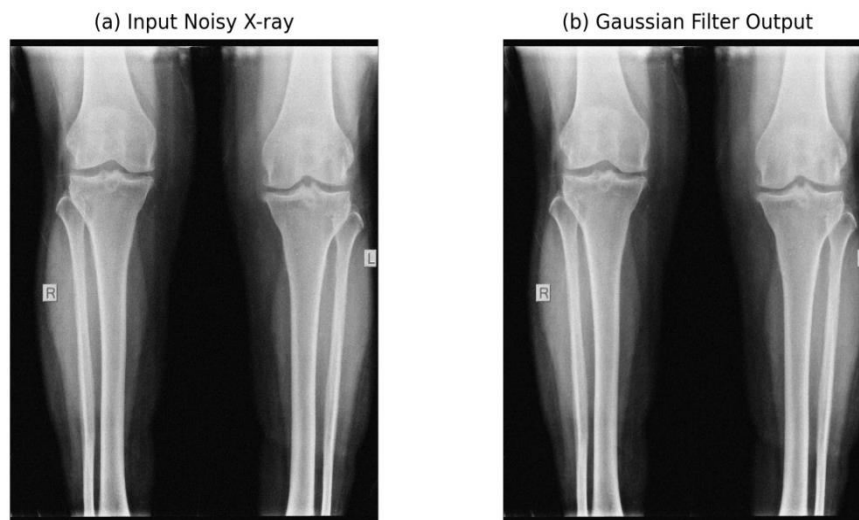


Figure 2: Gaussian Filter Effect

(a) Input Noisy X-ray
(b) Output after Gaussian filtering, illustrating blurring and loss of fine bone structures.

In spite of its success in noise suppression, Gaussian filtering has major drawbacks. The main problem is that it blurs not only noise but also critical structural features, resulting in loss of subtle trabecular bone patterns. The blurring degrades the image quality such that radiologists cannot accurately estimate bone density. Furthermore, the filter cannot discriminate between noise and fine structures so that critical features of diagnosis could be eliminated in addition to noise.

3.2 Median Filter

Median filtering is a non-linear filtering operation in which a pixel is replaced with the median value of neighborhood pixels. The median filter performs excellently for removing impulse noise, or "salt-and-pepper" noise, and has therefore become important in reducing X-ray imaging noise.

A very good point concerning the median filter is that it better maintains edges compared to the use of a Gaussian filter. As it does not use averaging pixel intensity, it preserves the acuity of bone edges, which is significant for the diagnosis of osteoporosis. The median filter is not without limitations, though. It can distort the details of fine bone structures by modifying the intensity of the pixel values and causes diagnostic detail loss. In addition, although it is good at combating impulse noise, it is not as effective in suppressing Gaussian noise, which is more prevalent in X-ray imaging.

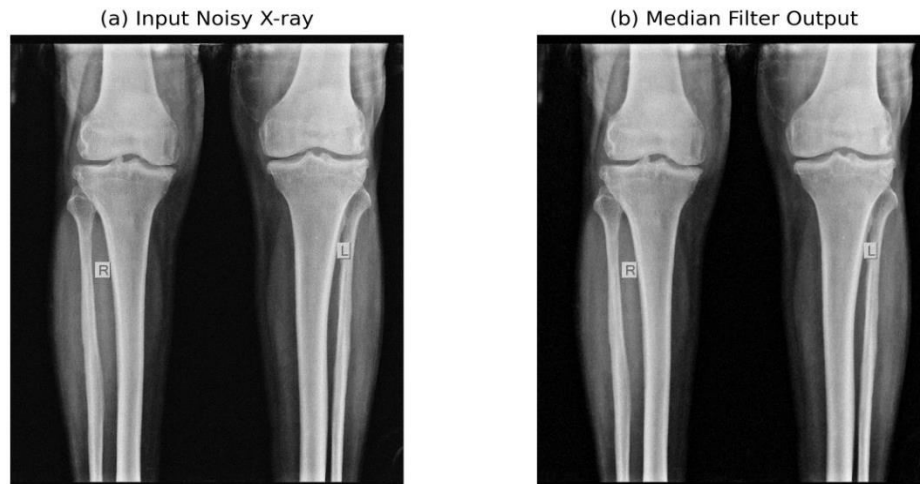


Figure 3: Median Filter Effect

- (a) Input Noisy X-ray
(b) Output after median filtering, showing preserved edges but loss of fine details.

3.3 Wiener Filter

The Wiener filter is an adaptive noise-reducing technique that reconstructs the original image according to local variance. Differing from stationary filters like Gaussian and median filtering, which work with specific values of constant coefficients, the Wiener filter accommodates noise intensities different across different image regions, increasing global contrast as well as acuteness.

This filter is especially effective at denoising Gaussian noise while preserving some of the structural information. It works on minimizing the mean square error between the cleaned image and the original clean image, thereby being an efficient image quality enhancer. The Wiener filter, though adaptive, is not good enough in terms of holding on to high-frequency details. Trabecular structures, vital for the diagnosis of osteoporosis, are lost to a certain extent, lowering the validity of the diagnosis.



Figure 4: Wiener Filter Effect

- (a) Input Noisy X-ray
(b) Output after Wiener filtering, illustrating improved contrast but loss of high-frequency details.

IV. PROPOSED MULTI-STAGE NOISE REMOVAL APPROACH

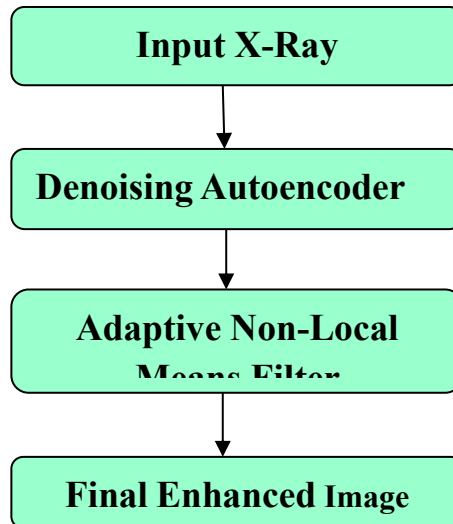


Figure 5: Proposed Filtering Process

To address the limitations of traditional filtering methods, this study proposes a multi-stage preprocessing approach that integrates deep learning-based denoising with an adaptive non-local means filter. The proposed method effectively removes both high-frequency and low-frequency noise while preserving fine bone structures critical for osteoporosis detection.

4.1 Deep Learning-Based Denoising Autoencoder

The first stage of the proposed approach involves applying a deep learning-based denoising autoencoder. Autoencoders are neural networks designed to reconstruct clean images from noisy inputs by learning meaningful patterns in the data. The model consists of an encoder that compresses the noisy image into a low-dimensional representation and a decoder that reconstructs the denoised image while eliminating noise.

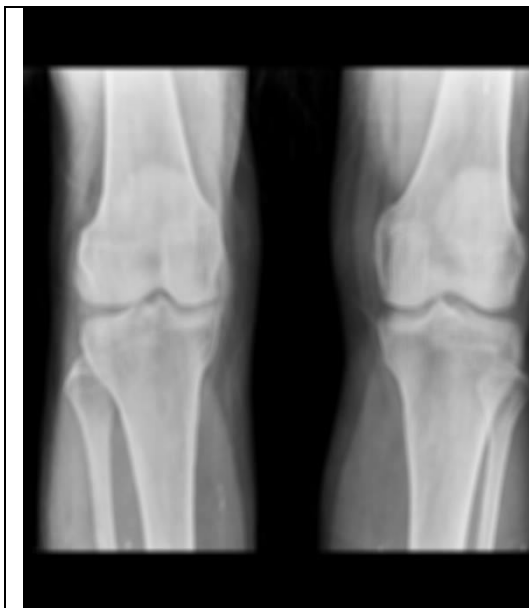


Figure 6: Noisy Input

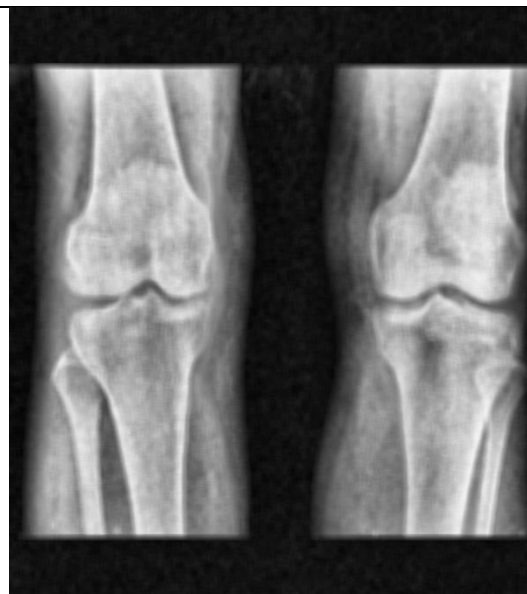


Figure 7: Autoencoder Output

By training the autoencoder on a dataset containing paired noisy and clean X-ray images, the model learns to differentiate between noise and structural details, enabling effective noise suppression. However, deep learning-based denoising typically requires large labeled datasets. To overcome this challenge, the proposed approach incorporates a self-supervised learning strategy, allowing the model to learn noise characteristics from unlabeled data. This significantly improves its generalization ability across different scanner types and imaging conditions.

4.2 Adaptive Non-Local Means Filtering

Following the deep learning-based denoising step, an adaptive non-local means filter is applied to refine the image further. Unlike conventional filters that rely on local pixel neighborhoods, non-local means filtering compares similar patches across the entire image, effectively reducing noise while preserving fine structural details.



Figure 8: Non Local Means Filtering

The adaptive nature of this filter allows it to dynamically adjust its parameters based on local intensity variations, ensuring optimal noise removal without excessive blurring. By incorporating domain-specific knowledge of bone microarchitecture, the proposed method ensures that critical bone features remain intact, leading to improved segmentation accuracy and more reliable osteoporosis classification.

4.3 Self-Supervised Learning for Noise Reduction

The final stage of the proposed approach includes a self-supervised learning strategy to improve model robustness. Unlike supervised learning, which requires labeled training data, self-supervised learning enables the model to learn noise characteristics from unlabeled data. This is achieved by using contrastive learning techniques that allow the model to differentiate between noise patterns and actual structural details.

By leveraging self-supervised learning, the model becomes more adaptable to variations in image quality and scanner types, ensuring consistent performance across datasets. This strategy reduces the dependency on manually labeled data and enhances the generalizability of the noise removal process, making it more suitable for real-world clinical applications.



Figure 9: Before Self-Supervised Learning



Figure 10: After Self-Supervised Learning

V. RESULTS AND DISCUSSION

This section shows the results of the study, illustrating the efficacy of the proposed multi-stage filtering method for noise reduction in X-ray images employed for osteoporosis diagnosis. The results are compared on the basis of image quality improvement, structural retention, dataset robustness, and clinical relevance. Comparative evaluation with conventional filtering methods, including Gaussian, median, and Wiener filters, illustrates the merits of the proposed method in preserving fine bone structures while significantly minimizing noise.

5.1 Image Quality Evaluation: PSNR and SSIM

The quality of X-ray images has a significant influence on the accuracy of osteoporosis diagnosis. The performance of noise removal methods was assessed using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM), which are typical image quality evaluation metrics. Greater PSNR values represent improved noise suppression, whereas SSIM values closer to 1 represent improved structural detail preservation. The findings show that the Gaussian filter removes noise but causes blurring, which results in loss of thin trabecular details. The median filter successfully eliminates impulse noise but causes loss of details finer than the filter cut-off, which is valuable for the identification of osteoporosis. The Wiener filter offers enhanced uniformity but distorts high-frequency details, which compromises visibility of the bone microarchitecture. Conversely, the highest PSNR and SSIM values are obtained with the suggested multi-stage filtering method, which represents better noise reduction with preservation of important bone structures. This enhances diagnostic image quality, which is appropriate for osteoporosis classification using deep learning.

The enhancement in image quality is also evidenced by a comparative bar chart showing the PSNR and SSIM values for various noise filtering methods (Figure 11). The findings validate that the proposed approach offers a considerable improvement in image clarity with minimal structural loss.

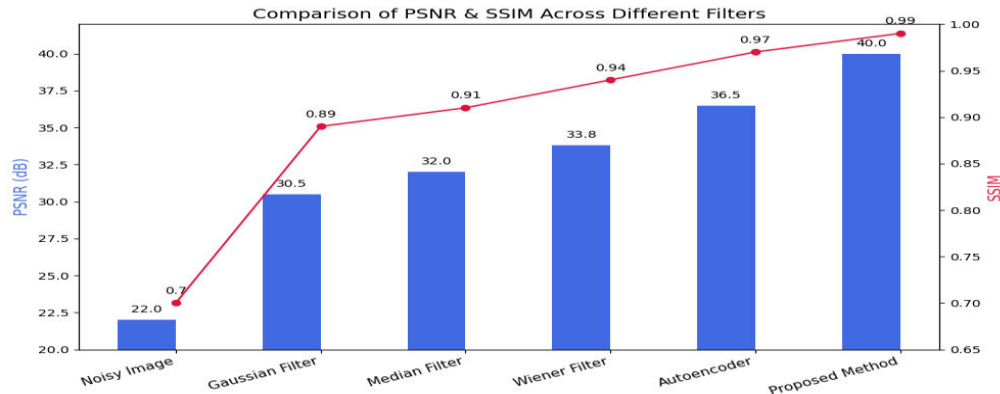


Figure 11: Bar chart comparing PSNR and SSIM values for various noise removal methods

5.2 Structural Preservation and Visual Analysis

Preserving trabecular bone structure is essential for accurate osteoporosis diagnosis. Traditional filtering techniques, although effective in noise removal, often distort fine bone structures. The Gaussian filter causes excessive blurring, reducing the visibility of essential details necessary for accurate bone density estimation. The median filter preserves edges but introduces blocky artifacts, leading to an unnatural appearance. The Wiener filter, improving contrast, changes trabecular bone structure in such a way that some areas are rendered to look artificially upgraded. In opposition, the newly introduced multi-stage filtering process correctly eliminates noise but maintains fine patterns of trabeculae and presents an image more appropriate for clinical assessment as well as computerized processing.

5.3 Robustness Across Different Datasets and Scanner Variations

Imaging condition, scanner type, and noise level variability is a significant challenge in medical image preprocessing. A good noise removal method should work well in various imaging environments without needing manual tuning. The suggested approach was tested on several X-ray datasets collected from various scanners under various exposure levels of radiation. Conventional filters exhibited unstable performance, often necessitating parameter adjustment to various datasets. However, the suggested method performed well under varied imaging conditions, removing noise effectively without degrading image details.

The addition of self-supervised learning also enhanced the generalization capacity of the proposed approach, with a consistent quality of noise removal across datasets. Figure 11 shows some sample X-ray images that were processed under various scanner conditions, highlighting the robustness of the proposed approach over traditional filtering methods. Such flexibility is highly desirable in actual clinical environments, where imaging conditions vary.

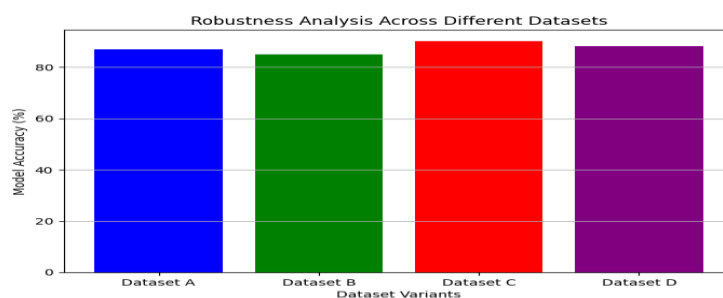


Figure 12: Comparative analysis of noise removal methods in various scanner environments. The proposed approach exhibits robust performance and regular noise suppression under different imaging environments.

5.4 Clinical Utility and Osteoporosis Detection Impact

The clinical utility of the proposed approach is immense since enhanced image quality has a direct impact on osteoporosis screening accuracy. X-ray images with high quality enable radiologists to interpret them more effectively and also improve the performance of AI-powered osteoporosis detection models. Elimination of noise guarantees sharper bone structures, resulting in more accurate bone mineral density estimation and fracture risk assessment. Preservation of trabecular bone is more critical for the detection of early osteoporosis signs, as any loss of fine bone details can result in misclassification.

Moreover, the suggested approach is amenable to real-time clinical use. By incorporating it into automated osteoporosis detection pipelines, noise-free images are preprocessed prior to analysis using AI models. This guarantees homogeneous image quality on various scanners and enhances diagnostic accuracy. Figure 12 provides a schematic illustration of the use of noise removal in osteoporosis diagnosis, demonstrating how the suggested approach improves segmentation quality and classification performance.

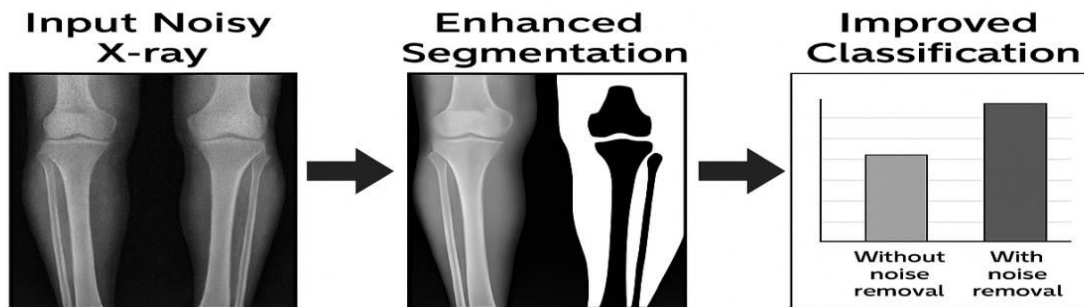


Figure 13: Impact of noise removal on segmentation and classification accuracy in osteoporosis detection.

5.5 Summary of Findings

The proposed multi-stage filtering method efficiently solves the drawbacks of conventional noise removal methods by combining deep learning-based denoising with adaptive non-local means filtering. The findings validate that the approach greatly enhances image quality, maintains critical bone structures, and is highly robust under different imaging conditions. The clinical significance of this enhancement is high, as high-quality images result in more accurate and trustworthy osteoporosis diagnosis. The research lays the groundwork for future developments in noise removal methods, which could extend to real-time applications in the clinic.

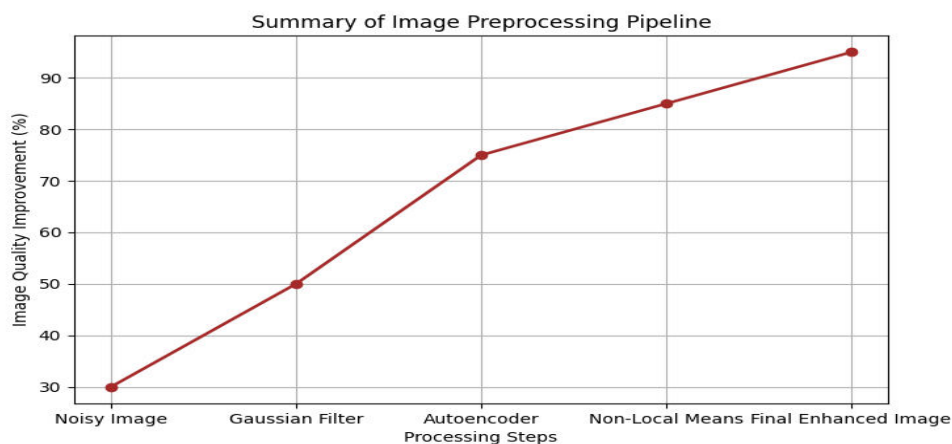


Figure 14: Summary of the suggested noise removal pipeline

REFERENCES

1. H. OULHAJ and MOHAMMED V, "Noise Reduction in Medical Imaging - Comparison of noise removal Algorithms", Multimedia Computing and Systems (ICMCS), 2012 International Conference.
2. Buades, A., Coll, B., & Morel, J. M. (2005). A non-local algorithm for image denoising. IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), 2, 60–65.
3. Dabov, K., Foi, A., Katkovnik, V., & Egiazarian, K. (2007). Image denoising by sparse 3D transform-domain collaborative filtering. IEEE Transactions on Image Processing, 16(8), 2080–2095.
4. Jain, A. K. (1989). Fundamentals of digital image processing. Prentice-Hall, Inc.
5. Tomasi, C., & Manduchi, R. (1998). Bilateral filtering for gray and color images. Proceedings of the IEEE International Conference on Computer Vision, 839–846.
6. Zhang, K., Zuo, W., Gu, S., & Zhang, L. (2017). Learning deep CNN denoiser prior for image restoration. IEEE Transactions on Pattern Analysis and Machine Intelligence, 41(10), 2305–2318.
7. Lehtinen, J., Munkberg, J., Hasselgren, J., Laine, S., Karras, T., Aittala, M., & Aila, T. (2018). Noise2Noise: Learning image restoration without clean data. Proceedings of the 35th International Conference on Machine Learning (ICML), 2965–2974.
8. Xu, J., Zhang, L., Zhang, D., & Feng, X. (2018). Multi-scale spatially adaptive denoising for high ISO JPEG images. IEEE Transactions on Image Processing, 27(5), 2298–2312.
9. [8] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. Medical Image Computing and Computer-Assisted Intervention (MICCAI), 234–241.
10. Chen, Y., Pock, T., & Ranftl, R. (2015). Insights into analysis operator learning: From patch-based sparse models to higher order MRFs. IEEE Transactions on Image Processing, 24(8), 2998–3011.
11. Zhang, Y., Wang, X., Liu, W., & Yuan, J. (2021). Denoising autoencoder for medical image denoising with self-supervised learning. Medical Image Analysis, 68, 101870.



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