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Medical Image Denoising Using the Cuckoo Optimization Algorithm

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ABSTRACT

Medical images acquired using imaging modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and ultrasound constitute essential sources of information for clinical diagnosis, treatment planning, and quantitative biomedical analysis. Nevertheless, these images are inevitably affected by different types of noise and acquisition-related degradations, which can obscure anatomical structures, distort intensity information, and adversely affect subsequent image-processing and diagnostic tasks. Consequently, effective noise reduction while preserving diagnostically important structures remains a fundamental challenge in medical image processing. Among conventional denoising techniques, the bilateral filter has attracted considerable attention because of its ability to suppress noise while preserving edges by jointly incorporating spatial proximity and intensity similarity into the filtering process. Despite these advantages, the performance of the bilateral filter is highly dependent on the appropriate selection of its parameters and filtering window size. Fixed or manually selected parameters may not provide satisfactory performance across images characterized by different noise distributions and intensities. To overcome this limitation, this study proposes a modified and adaptive bilateral filtering framework in which the filter parameters and weighting coefficients are automatically optimized using the Cuckoo Optimization Algorithm (COA). The proposed hybrid approach exploits the global optimization capability of COA, inspired by the parasitic breeding behavior of cuckoos, to efficiently search the parameter space and identify an appropriate combination of bilateral-filter coefficients. An objective fitness function based on image-quality measures is employed to guide the optimization process toward improved denoising performance. The proposed framework is evaluated experimentally on benchmark medical image datasets and compared with conventional and alternative filtering approaches. Both quantitative and qualitative assessments demonstrate that the proposed method provides superior noise suppression while maintaining important anatomical structures, fine textures, and sharp image boundaries. In particular, the method exhibits robust performance under high-density noise conditions, where excessive smoothing can substantially degrade clinically relevant information. The results demonstrate the effectiveness of integrating metaheuristic optimization with edge-preserving filtering and indicate that the proposed framework can improve the quality and interpretability of medical images for subsequent computer-aided analysis and clinical applications.

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1. INTRODUCTION

Medical images such as MRI, CT, mammography, and ultrasound are critical tools for the diagnosis and monitoring of diseases. However, these images are inherently susceptible to various types of noise, the most prominent of which are speckle and Gaussian noise. The presence of noise in medical imagery can degrade visual quality, lead to diagnostic errors by clinicians, and necessitate re-imaging. This not only increases costs, examination time, and radiation doses but can also compromise patient safety. Therefore, denoising medical images is not only a scientific necessity but also a practical requirement in the public health sector [1-2].

The paramount challenge in medical image denoising is achieving an optimal balance between effective noise reduction and the preservation of vital structural details. Although many traditional filtering methods successfully suppress noise, they often suffer from blurred boundaries, lost edges, and a reduction in fine textural details. In clinical applications, such as the early detection of small tumors or the evaluation of vascular lesions, this degradation can lead to false results. Furthermore, variations in imaging equipment quality and patient conditions add further complexity to the denoising process [3-5].

To address these challenges, diverse methodologies have been proposed in recent years. Linear filters, median filters, adaptive filters, and wavelet transform-based methods are among the most widely used approaches. One effective method is the bilateral filter, which simultaneously utilizes spatial and intensity information to suppress noise. While this filter has partially mitigated the edge-blurring problem, its performance depends heavily on the proper selection of parameters; inappropriate tuning can lead to reduced sharpness and the loss of fine structures [6-7].

To overcome these limitations, nature-inspired optimization algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and the Cuckoo Optimization Algorithm (COA) have attracted significant attention. By performing an adaptive search within the parameter space, these algorithms can determine the global optimal values for filter weights and coefficients. Integrating optimization algorithms not only enhances image quality but also enables filters to adapt dynamically to diverse medical imaging modalities and conditions. Consequently, these paradigms offer an intelligent and robust solution for noise reduction without sacrificing critical clinical information [8-9].

The combination of advanced filters and intelligent optimization algorithms holds great promise for the future of medical image processing. These hybrid frameworks have found widespread application in the early detection of cancer, brain tissue analysis, cardiovascular disease evaluation, and image analysis in robotic surgery. Furthermore, implementing these methods can shorten diagnostic times, reduce healthcare costs, and improve the overall quality of healthcare services. Given the rapid advancements in parallel computing and machine learning, optimization-based approaches are expected to become a cornerstone of medical image processing in the near future [10-11].

2. EXISTING METHODS

Enhancing image quality and reducing noise in medical images has remained a fundamental challenge in advanced image processing due to its direct impact on diagnostic accuracy. For instance, Haddadnia et al. (2015) demonstrated how precise preprocessing and segmentation of suspicious tissues in mammographic images can significantly improve the true positive detection rate [12].

In a similar vein, Shakeri et al. (2025) emphasized the importance of extracting structural features by integrating hybrid deep architectures, suggesting the use of complementary optimization techniques to enhance the performance of medical imaging models [13]. Turning specifically to noise reduction, Zamani et al. (2021) addressed the limitations of traditional filtering methods by introducing an advanced intelligent framework; this approach utilizes a Genetic Algorithm (GA) to find the optimal threshold in the wavelet domain for denoising X-ray images [14]. Given the success of swarm intelligence and smart optimization methods in improving quality metrics such as the Structural Similarity Index Measure (SSIM) and Peak Signal-to-Noise Ratio (PSNR) replacing legacy evolutionary algorithms with metaheuristic algorithms that exhibit higher convergence rates appears to be an effective strategy. Accordingly, the present study aims to overcome existing limitations by developing an efficient medical image denoising method based on the Cuckoo Optimization Algorithm (COA) to suppress severe noise while preserving edge details and vital image structures in an optimal manner.

To preserve edges while reducing image noise, a Laplacian pyramid-based cross-pseudo-bilateral filter was introduced in [1]. In this method, the original image and its filtered version are first decomposed into multiple levels using a Laplacian pyramid. The filtered version is obtained via an adaptive Wiener filter. A cross-pseudo-bilateral filter is then applied at each level, where the filtered image serves as the "true" reference guidance. To adaptively tune the parameters, the noise variance at each level is estimated and mapped to the photometric spread parameter of the bilateral filter. Experimental results indicated that this algorithm outperforms both the adaptive Wiener filter and the classical bilateral filter in objective and subjective evaluations.

In [2], to address the constraints of single-frame denoising methods, a novel adaptive spatial filtering technique for multi-frame images was proposed. In this approach, each frame is first processed using adaptive filters to reduce noise while preserving important details. Subsequently, similar pixels across multiple frames are averaged to complete the denoising process and mitigate cartoon-like artifacts. This study evaluated three configurations: an adaptive filter on a single frame, simple multi-frame averaging, and a hybrid approach combining the adaptive filter with multi-frame averaging. The results demonstrated that the hybrid method yields superior efficiency in noise reduction and image quality preservation compared to the other two configurations.

In the domain of medical imaging, preserving edges and structural details is of paramount importance, as these features are vital for accurate clinical diagnosis. The bilateral filter is a well-known technique for edge-preserving smoothing. However, its noise removal performance is not entirely satisfactory under high noise levels. The root cause is that the classical bilateral filter operates directly on pixel gray levels, which propagates noise during the filtering process. To resolve this, a novel approach was presented in [3], where the bilateral filter is applied conditionally to the image context. In this framework, the range filter is defined over a smoothed context of the image rather than the direct, noisy gray-level intensities, thereby significantly suppressing noise propagation. Experiments conducted on real medical images confirmed the robust efficiency of this method compared to conventional techniques.

In [4], a implementation of the bilateral filter for image denoising was presented, targeting applications in computational photography. The bilateral filter is a non-linear technique capable of smoothing images without degrading sharp edges. The underlying principle of this filter is that each output pixel value is computed as a weighted sum of neighboring pixels in the input image. Essentially, it provides localized smoothing while preserving edge structures. Since convolution with a kernel is the fundamental step in linear, space-invariant image filtering, this filter operates as a type of low-pass filter that computes the local intensity average based on spatial proximity and radiometric similarity. The modeling of this filter was presented in the Simulink environment as well as implemented in MATLAB.

On the other hand, clinical data derived from Magnetic Resonance Imaging (MRI) often suffer from quality degradation due to random noise inherent in the measurement process, which compromises the accuracy and reliability of automated analysis methods. Consequently, the application of denoising techniques to boost the signal-to-noise ratio and enhance image quality is an unavoidable necessity. Despite extensive research, denoising remains a serious challenge at the intersection of mathematical analysis and statistics. Many advanced existing methods yield optimal results only if the noise or image model satisfies the underlying algorithmic assumptions; under general conditions, their performance drops, and they may even eliminate fine details or introduce unwanted artifacts.

In this regard, reference [5] presented an extension of the classical bilateral filter, introducing a multi-resolution bilateral filter based on the combination of wavelet transform subbands. This multi-resolution framework significantly enhances filter performance in noise reduction and image quality improvement. By leveraging a combination of wavelet subbands, image details are better preserved, and noise artifacts are eliminated with higher precision. Quantitative validation of this algorithm was performed on synthetic datasets generated by the BrainWeb simulator. Comparative results against other conventional methods including non-linear diffusion, fourth-order partial differential equations (PDEs), total variation (TV), non-local means (NLM), wavelet thresholding, and the classical bilateral filter demonstrated that the multi-resolution bilateral filter provides superior denoising performance and noticeably elevates the quality of reconstructed images.

In [6], an efficient denoising algorithm for corrupted images was proposed, which leverages a combination of wavelet thresholding and a joint bilateral filter in the spatial domain. Wavelet-based methods perform well in image denoising but typically introduce low-frequency artifacts and ringing effects around edges, which are dependent on the base wavelet structure. Conversely, spatial-domain algorithms often provide higher denoising quality with fewer artifacts, but at a steep computational cost. To reduce this computational overhead, the proposed method designs an efficient joint bilateral filter applied to the results of the wavelet-based denoising rather than processing the noisy image directly. Specifically, the joint bilateral filter is executed on the approximation subband (low frequency) of the wavelet-decomposed image, while wavelet thresholding is applied to the detail subbands. The algorithm was tested on a set of standard images, and its efficiency was validated using the Peak Signal-to-Noise Ratio (PSNR) metric, demonstrating highly favorable performance.

Reference [7] introduced a novel denoising method that combines the bilateral filter with non-local means (NLM). Although NLM is a widely used denoising technique, its primary drawback is the over-smoothing of edges. To address this issue, the authors utilized a fast and efficient NLM approach using approximate nearest-neighbor fields, while enhancing edge content via a tailored joint bilateral filter. Within this framework, smooth regions of the image are denoised using NLM, whereas edge details are efficiently reconstructed by the bilateral filter. Furthermore, to avoid complexity in parameter selection, a noise estimation step is performed prior to filtering. Experimental results indicated that this algorithm performs exceptionally well on images with high noise levels while preserving the quality of edge reconstruction.

3. PROPOSED METHOD

Image denoising is a pivotal task in image processing and computer vision. Noise can stem from suboptimal sensor conditions, hardware limitations, or environmental factors, drastically degrading the quality of downstream analyses. A primary challenge in denoising is the preservation of edges and structural details. While straightforward methods like mean or Gaussian filtering effectively reduce noise, they cause edge blurring and compromise structural integrity [15-16].

The Bilateral Filter was introduced as a prominent denoising technique to overcome this limitation. It is a non-linear method that computes the output intensity of a pixel as a weighted average of its spatial neighbors, incorporating both spatial distance and radiometric (intensity) similarity. Consequently, neighboring pixels contribute to the smoothing process based not only on their geometric proximity but also on their grayscale similarity to the center pixel. This feature allows the filter to preserve sharp edges while effectively smoothing uniform regions.

The primary application of the bilateral filter lies in domains where preserving image detail is critical, such as computational photography, medical image processing, and preprocessing for computer vision. In medical modalities like MRI or CT, maintaining edges and fine textures is essential because vital diagnostic information resides in these structures. In this context, the bilateral filter can attenuate noise without destroying clinical features.

Despite its advantages, the bilateral filter possesses certain limitations. Its most notable drawback is a high computational overhead, which arises from the need to calculate weights for all neighboring pixels. Furthermore, its performance may degrade under high noise levels, potentially leading to residual noise or halo artifacts around sharp edges. To remedy these shortcomings, extensive research has focused on enhancing the filter or hybridizing it with techniques such as the wavelet transform, non-local means, and machine learning algorithms.

Overall, the bilateral filter remains an efficient tool for edge-preserving denoising and continues to be a subject of widespread research. Developing multi-resolution versions, accelerating execution via mathematical approximations, and integrating it with modern deep learning frameworks represent highly active research trajectories in recent years.

The Cuckoo Optimization Algorithm (COA) is a nature-inspired metaheuristic [17]. It is modeled after the obligate brood parasitism behavior of certain cuckoo species, which lay their eggs in the nests of other host birds. Cuckoos deposit their eggs in host nests, and only the eggs that closely resemble those of the host bird stand a chance of survival. This evolutionary process inspires a search mechanism for optimization problems, where higher-quality solutions survive and poorer solutions are systematically eliminated.

A core concept within COA is the utilization of Lévy flights. This type of flight behavior, observed in various birds and insects in nature, features a combination of short, localized movements punctuated by occasional, random long-distance jumps. This characteristic enables the algorithm to simultaneously explore the search space thoroughly and exploit local regions, preventing it from becoming trapped in local optima. As a result, COA exhibits robust global search capabilities and has demonstrated superior performance over traditional optimization methods across numerous complex problems.

The primary advantage of the Cuckoo Optimization Algorithm lies in its implementation simplicity and its minimal number of tunable parameters. Unlike some evolutionary algorithms such as Genetic Algorithms or Particle Swarm Optimization COA requires only a few primary parameters, such as the number of cuckoos and the egg discovery/replacement rate. This efficiency makes it highly applicable to a broad spectrum of optimization problems, including numerical optimization, engineering design, scheduling, and machine learning tasks.

Notwithstanding its strengths, the Cuckoo Optimization Algorithm has limitations. For instance, in high-dimensional problems or functions with highly complex search landscapes, its convergence rate can slow down. Consequently, enhanced variants have been developed, enabling hybridization with other algorithms like GA, PSO, and deep learning architectures. These hybrid configurations bolster the algorithm's exploration and exploitation capabilities, yielding faster and more precise results.

In conclusion, the Cuckoo Optimization Algorithm is recognized as a modern, high-performance metaheuristic. Its defining characteristics are its capacity to discover global optima and evade local traps, coupled with high simplicity and flexibility. For these reasons, the algorithm has secured a prominent position in both academic research and industrial applications.

The proposed optimization framework for tuning the bilateral filter parameters via COA is structured as follows:

A. Optimization Problem Definition

- The key parameters of the bilateral filter, namely the spatial parameter σs and the radiometric (intensity) parameter σr, are selected as the decision variables for optimization.
- The objective function is defined based on image quality metrics, such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), or a hybrid combination of both, to quantify the trade-off between noise reduction and detail preservation.

B. Initialization of the Cuckoo Population

- A set of initial solutions (randomly generated values for the filter parameters within predefined boundaries) is generated to represent the cuckoo eggs.
- Each candidate solution corresponds to a specific parameter configuration (σs, σr) for the bilateral filter.

C. Application of Lévy Flights and Generation of New Solutions

- New positions (updated filter parameters) are generated using Lévy flights to thoroughly explore the search space.
- This stage combines local search (to refine current elite solutions) and global search (to escape local optima).

D. Quality Evaluation of Candidate Solutions

- For each candidate parameter set, the bilateral filter is applied to the noisy input image.
- The quality of the resulting denoised image is measured using the selected objective metric.
- This calculated quality score is assigned as the fitness value of the corresponding cuckoo.

E. Replacement and Natural Selection

- Weak eggs (suboptimal filter configurations) are discarded with a given probability and replaced by newly generated candidate solutions.
- Superior eggs are preserved for subsequent generations.

F. Iteration Until Convergence

- The processes of solution generation, Lévy flights, evaluation, and selection are iteratively executed until a termination criterion is satisfied (e.g., reaching a maximum number of iterations or observing stagnation in quality improvement).

G. Selection of Optimal Parameters

- Upon termination, the best-performing solution obtained (the optimal configuration of σs and σr) is selected as the final parameter set.
- These optimized values are utilized for the final filtering pass on the medical images to produce the high-quality, denoised output.

4. SIMULATION RESULTS

The proposed and benchmark methods were implemented using MATLAB (MathWorks, Inc.). The hardware environment utilized for the simulations consisted of an Intel(R) Core™ i5-4460 CPU @ 3.2 GHz processor equipped with 16 GB of RAM.

A sample implementation of this method is illustrated in Figure 1. The noisy signal profile is shown in Figure 2. The denoised signal reconstructed by the proposed method is presented in Figure 3, where the initial and final SSIM values are 0.037 and 0.64, respectively. The convergence behavior during the optimization process is depicted in Figure 4.

The BrainWeb database was introduced in 2000 [18]. This repository contains simulated 3D human brain MRI data, providing researchers and developers of medical image processing algorithms with a standardized, controlled environment to test and validate their methodologies. BrainWeb images capture the primary anatomical structures of the brain, including white matter, gray matter, and cerebrospinal fluid (CSF). It offers the flexibility to simulate various MRI modalities, including T1-, T2-, and proton density (PD)-weighted contrasts. Furthermore, users can adjust Gaussian noise levels and intensity inhomogeneity (bias field) percentages, enabling rigorous evaluation of noise reduction and image enhancement algorithms.

To evaluate image quality after applying the filters and the proposed optimization framework, the Structural Similarity Index Measure (SSIM) was employed to quantify the structural similarity between the original reference image and the reconstructed output. The SSIM metrics obtained from the baseline methods compared against the proposed algorithm are summarized in Figure 5. As illustrated in the figure, the proposed algorithm successfully increased the SSIM value to 0.66, demonstrating a substantial improvement over the reference methods. This elevate in the SSIM score indicates superior preservation of structural boundaries and fine texture patterns post-processing. Consequently, the proposed algorithm not only suppresses image noise effectively but also retains critical structural components and edge definitions. The empirical findings demonstrate that optimizing filter parameters via the proposed framework under noisy conditions yields superior performance compared to existing approaches, underscoring the high efficiency of the proposed method in processing medical images while preserving structural integrity.

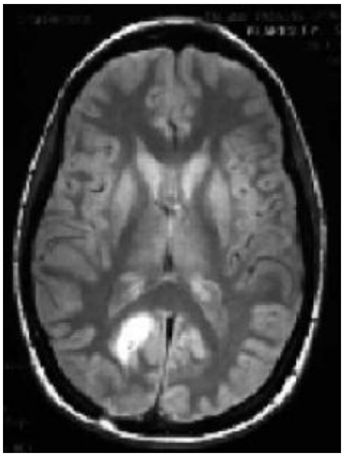

Fig. 1. Original signal.

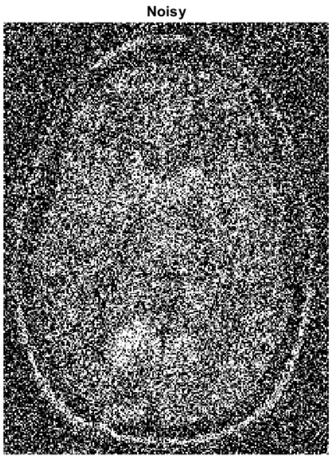

Fig. 2. Noisy signal.

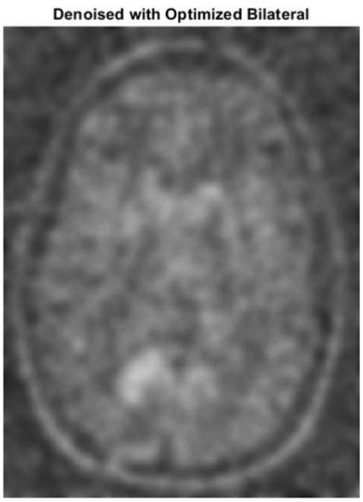

Fig. 3. Denoised signal using the proposed method.

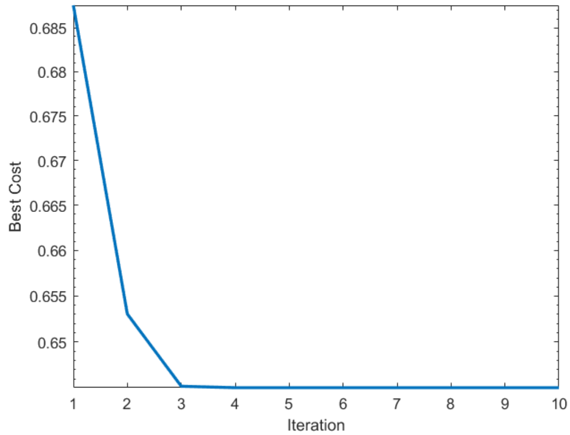

Fig. 4. Optimization process (Convergence curve).

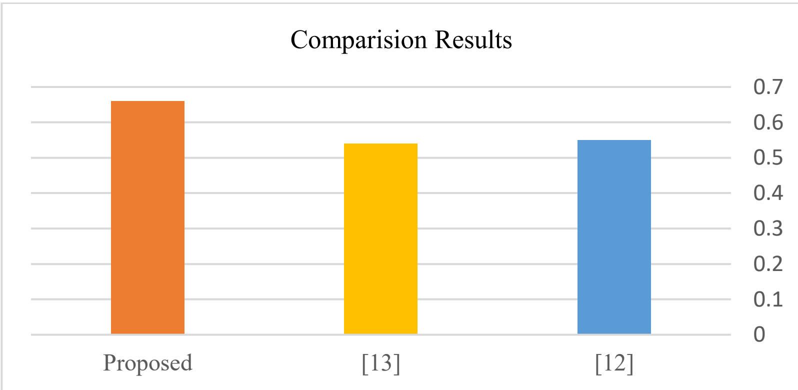

Fig. 5. Comparison between the proposed method and existing baseline methods.

5. CONCLUSION

In this research, an automated method for medical image denoising was presented, leveraging a bilateral filter optimized by the evolutionary Cuckoo Optimization Algorithm (COA). The primary objective of this study was to achieve effective noise reduction while simultaneously preserving vital image details and structural boundaries. The simulation results demonstrate that utilizing COA to optimize the filter's parameters leads to a significant improvement in overall image quality. By defining an objective cost function based on the Structural Similarity Index Measure (SSIM), the algorithm successfully determined the optimal parameter configurations in an automated manner. Visual and quantitative comparisons confirm that noise is substantially suppressed, while sensitive edges and complex textures are preserved without degradation.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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REFERENCES

[1] Meng, W., Huisheng, Z., & He, H. (2008). A pseudo cross bilateral filter for image denoising based on Laplacian pyramid. In *2008 IEEE International Symposium on Knowledge Acquisition and Modeling Workshop* (pp. 235–238). IEEE. https://doi.org/10.1109/KAMW.2008.4810469

[2] Qinlan, X., & Hong, C. (2009). Image denoising based on adaptive filtering and multi-frame averaging filtering. In *2009 International Conference on Artificial Intelligence and Computational Intelligence* (pp. 523–526). IEEE. https://doi.org/10.1109/AICI.2009.490

[3] Liao, Z., Hu, S., Yu, Z., & Sun, D. (2010). Medical image blind denoising using context bilateral filter. In *2010 International Conference of Medical Image Analysis and Clinical Application* (pp. 12–17). IEEE. https://doi.org/10.1109/MIACA.2010.5528280

[4] Patil, P. D., & Kumbhar, A. D. (2015). Bilateral filter for image denoising. In *2015 International Conference on Green Computing and Internet of Things (ICGCIoT)* (pp. 299–302). IEEE. https://doi.org/10.1109/ICGCIoT.2015.7380477

[5] Mustafa, Z. A., & Kadah, Y. M. (2011). Multi resolution bilateral filter for MR image denoising. In *2011 1st Middle East Conference on Biomedical Engineering* (pp. 180–184). IEEE. https://doi.org/10.1109/MECBME.2011.5752095

[6] Bibina, V. C., & Viswasom, S. (2012). Adaptive wavelet thresholding & joint bilateral filtering for image denoising. In *2012 Annual IEEE India Conference (INDICON)* (pp. 1100–1104). IEEE. https://doi.org/10.1109/INDCON.2012.6420781

[7] Jith, O. U. N., & Babu, R. V. (2014). Joint bilateral filtering based non-local means image denoising. In *2014 International Conference on Signal Processing and Communications (SPCOM)* (pp. 1–5). IEEE. https://doi.org/10.1109/SPCOM.2014.6984014

[8] Olfa, M., & Nawres, K. (2014). Ultrasound image denoising using a combination of bilateral filtering and stationary wavelet transform. In *International Image Processing, Applications and Systems Conference* (pp. 1–5). IEEE. https://doi.org/10.1109/IPAS.2014.7043258

[9] Yu, H., Zhao, L., & Wang, H. (2009). Image denoising using trivariate shrinkage filter in the wavelet domain and joint bilateral filter in the spatial domain. *IEEE Transactions on Image Processing, 18*(10), 2364–2369. https://doi.org/10.1109/TIP.2009.2026685

[10] De Decker, A., Lee, J. A., & Verlysen, M. (2009). Variance stabilizing transformations in patch-based bilateral filters for Poisson noise image denoising. In *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 3673–3676). IEEE. https://doi.org/10.1109/IEMBS.2009.5334715

[11] Thakur, K., Damodare, O., & Sapkal, A. (2015). Hybrid method for medical image denoising using Shearlet transform and bilateral filter. In *2015 International Conference on Information Processing (ICIP)* (pp. 220–

224). IEEE. https://doi.org/10.1109/INFOP.2015.7489382

[12] Haddadnia, J., Rahmani-Seryasat, O., Ghayoumi-Zadeh, H., & Rabiee, H. (2015). An efficient method for detection of masses in mammogram images. *Cumhuriyet Üniversitesi Fen Edebiyat Fakültesi Fen Bilimleri Dergisi, 36*(3), 2269–2277.

[13] Shakeri, N., & Rahmani Seryasat, O. (2025). Improving medical image segmentation using a hybrid ResUNet-Transformer architecture for liver tumor detection. *Transactions on Machine Intelligence, 8*(1), 57–68. https://doi.org/10.47176/TMI.2025.57

[14] Zamani, M., Azadi, S., & Rahmani Seryasat, O. (2021). Noise reduction in medical X-ray images using wavelet and neural networks. *Transactions on Machine Intelligence, 4*(1), 36–52. https://doi.org/10.47176/TMI.2021.36

[15] Kaur, A., Singh, H., & Arora, D. (2017). An efficient approach for image denoising based on edge-aware bilateral filter. In *2017 4th International Conference on Signal Processing, Computing and Control (ISPCC)* (pp. 56–61). IEEE. https://doi.org/10.1109/ISPCC.2017.8269649

[16] Chaudhury, K. N., & Rithwik, K. (2015). Image denoising using optimally weighted bilateral filters: A SURE and fast approach. In *2015 IEEE International Conference on Image Processing (ICIP)*. IEEE. https://doi.org/10.1109/ICIP.2015.7350769

[17] Rajabioun, R. (2011). Cuckoo optimization algorithm. *Applied Soft Computing, 11*(8), 5508–5518. https://doi.org/10.1016/j.asoc.2011.05.008

[18] Cocosco, C. A. (1997). *BrainWeb: Online interface to a 3D MRI simulated brain database*. McConnell Brain Imaging Centre, Montreal Neurological Institute, McGill University.