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A Hybrid Denoising–Edge Detection Framework for Enhanced Medical Image Analysis

Tanusree Saha, Kumar Vishal

Abstract: ***High-quality medical imaging is indispensable for precise diagnosis and treatment planning, but it is confounded by noise and ill-defined edges that impede diagnostic consistency. Noise originating during acquisition, transmission, or reconstruction tends to obliterate delicate structures but makes existing edge detection schemes incapable of producing edge-line sharp and smooth where noisy features abound. It is imperative to resolve such complications to enhance clinical image interpretability and facilitate the development of sophisticated computer-aided diagnosis systems. This research presents a Hybrid Denoising–Edge Detection Framework that merges state-of-the-art filtering and localization of edges to enable better analysis of medical images. An early stage adopts a hybrid filtering methodology that combines Adaptive Median Filtering and Block-Matching and 3D (BM3D) filtering. Adaptive Median Filtering efficiently eliminates speckle and impulse noise while preserving edge detail effectively, and BM3D reduces additional Gaussian noise using collaborative patch-based denoising. Both utilise superior noise resilience without loss of structural fidelity. A hybrid edge detection methodology, combining the Sobel operator and the Canny detector, is incorporated into the final stage. Sobel operates effectively in localising strong gradient variations, while Canny applies non-maximum suppression and hysteresis thresholding to achieve optimal edge continuation. An edge fusion process gains both strategies' complementary strengths to produce sharper and more consistent edge maps. Experiments were carried out on MRI, chest X-ray, and mammography images corrupted by simulated Gaussian, salt-and-pepper, and speckle noise. Quality was compared quantitatively using Peak Signal-to-Noise Ratio (PSNR) against noise suppression, Structural Similarity Index (SSIM) against structural preservation, and Edge Connectivity Ratio (ECR) against continuity of edges supported by quality visual assessment.***

Keywords: ***Medical Image, Canny, Sobel, BM3D (Block Matching and 3D Filtering), Otsu, Adaptive Median.***

Abbreviations:
ECR: Edge Connectivity Ratio
SSIM: Structural Similarity Index
BM3D: Block-Matching and 3D
PSNR: Peak Signal-to-Noise Ratio

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I. INTRODUCTION

Medical image processing has become an essential element of contemporary healthcare, facilitating the detection of disorders, monitoring of progression, and formulation of effective treatments by physicians and researchers. The ability to obtain high-quality medical images is essential; nevertheless, these images often suffer degradation from various types of noise during acquisition, transmission, or reconstruction. This degradation obscures tiny details, undermines diagnostic reliability, and complicates subsequent analysis tasks, including segmentation, classification, and three-dimensional reconstruction. In clinical practice, minor aberrations in image quality might result in misinterpretation of anatomical features, delayed diagnoses, or inaccuracies in treatment planning. Noise removal, or denoising, has consequently become an essential pre-processing procedure in medical imaging. Conventional filtering techniques have been extensively utilised; nonetheless, they often face a compromise between efficient noise reduction and the retention of significant structural information. Over-smoothing from basic filters can eliminate nuanced diagnostic indicators, whereas inadequate denoising retains residual artefacts that conceal relevant information. This problem is particularly evident in modalities such as MRI, CT, and mammography, where intricate structures like tumour margins, microcalcifications, or vascular networks hold significant therapeutic relevance. The process of edge recognition is equally crucial, as it establishes the basis for recognising anatomical borders and areas of interest. Dependable edge detection facilitates precise delineation of organs, lesions, and problematic regions, hence aiding subsequent tasks such as segmentation, feature extraction, and computer-assisted diagnosis. Conventional edge detectors frequently exhibit suboptimal performance in noisy environments, resulting in fragmented, distorted, or erroneous edges. This undermines the continuity of structural boundaries and diminishes the therapeutic utility of processed images. The dual problem of noise reduction and edge retention highlights the need for hybrid methods that amalgamate the advantages of various techniques. By initially eliminating noise effectively and subsequently employing sophisticated edge recognition techniques, it is feasible to produce images that are both clear and architecturally precise. Hybrid frameworks attain this equilibrium by reducing the constraints of singular methodologies and amplifying their synergistic strengths. Adaptive filtering techniques can mitigate impulsive noise while preserving edge features, and sophisticated edge detectors guarantee precise, uninterrupted, and dependable border localisation. In recent years, the domain has been significantly impacted by the swift advancement of machine learning and deep learning techniques. Neural networks and data-driven designs exhibit exceptional adaptability in managing various imaging situations and accommodating fluctuations in noise levels and anatomical intricacy. These models have demonstrated the ability to enhance image quality, improve segmentation accuracy, and provide scalable solutions across several imaging modalities. Nonetheless, fully data-driven approaches frequently necessitate substantial training datasets, significant processing resources, and meticulous optimisation, potentially constraining their prompt clinical implementation. This study presents a hybrid system for denoising and edge detection specifically designed for medical imaging applications. The framework is engineered to mitigate various types of noise while maintaining robust, continuous, and diagnostically pertinent edges. The system attains an optimal balance between noise reduction and edge preservation through the integration of adaptive filtering and hybrid edge detection. The suggested methodology has been evaluated across various imaging modalities, including MRI, X-ray, and mammography, yielding improvements in both quantitative image quality metrics and qualitative diagnostic clarity. This framework seeks to deliver a robust, efficient, and clinically relevant solution that connects traditional filtering methods with advanced intelligent image processing models.

II. LITERATURE REVIEW

Medical image processing fundamentally depends on denoising and edge detection as critical procedures to improve diagnostic precision. Preliminary thresholding strategies, including adaptive methods, are essential in segmentation tasks. Sujatha and Mahalakshmi [1] recently proposed an adaptive thresholding technique for medical picture segmentation that enhanced foreground-background differentiation while preserving structural integrity. Gaussian smoothing remains prevalent; yet, conventional methods can obscure intricate anatomical characteristics. Varghese et al. [2] introduced an enhanced Gaussian smoothing technique designed for medical imaging, effectively reducing noise while preserving structural integrity. Anisotropic diffusion has been acknowledged as a robust method for edge-preserving denoising. Contemporary implementations, exemplified by the framework developed by Agudelo et al. [3], re-examine anisotropic diffusion to enhance structural preservation while mitigating over-smoothing. Multiscale methodologies, like wavelet thresholding, have also advanced. Yang et al. [4] provide a contemporary viewpoint on wavelet thresholding, demonstrating its ability to manage noise at various resolutions in clinical imaging. The BM3D approach continues to be highly prominent among cutting-edge algorithms because of its collaborative filtering mechanism. Maggioni et al. [5] enhanced BM3D for medical imaging, demonstrating substantial advancements in Gaussian noise reduction, whereas Buades et al. [6] presented an exhaustive analysis of patch-based denoising techniques, emphasising BM3D and its derivatives as performance standards. Nonetheless, processing complexity constrains its application in real-time clinical operations. Recent years have seen a resurgence in the examination of adaptive median filtering to mitigate impulse noise. Prabhakar et al. [7] established that adaptive median filtering efficiently mitigates salt-and-pepper noise while maintaining diagnostic information, including minor lesions. Edge detection is essential, serving as the basis for segmentation and boundary extraction. Hossain et al. [8] examined recent developments in edge detection for medical imaging and emphasised the shortcomings of traditional Sobel and Canny detectors in noisy environments. To address these challenges, Xu et al. [9] highlighted the significance of deep learning-based edge detectors, which incorporate contextual information and surpass traditional operators in terms of resilience and continuity. Comparative investigations, such as those conducted by Shi [10], further validate that hybrid methodologies, which integrate adaptive filtering with traditional edge detection, enhance both sharpness and continuity. The incorporation of deep learning has substantially improved medical image enhancement. Sarwar et al. [11] examined denoising techniques utilising deep learning, demonstrating improvements in CT, MRI, and X-ray imaging. Likewise, Singh et al. [12] emphasised the adaptability of deep neural networks for denoising, segmentation, and edge detection, underscoring their clinical relevance. Zhang et al. [13] recently examined the advancement of U-Net and transformer-based models, which demonstrated enhanced retention of intricate structures relative to traditional methods.

III. METHODOLOGY

The proposed framework is a two-stage hybrid pipeline consisting of (i) noise reduction using hybrid filtering and (ii) boundary enhancement using hybrid edge detection. The design ensures that noise is suppressed before edge extraction, thereby preventing spurious edges while maintaining structural fidelity. The following steps present the overall system architecture.

A. Overview of the Proposed Method

i. Input medical image (*MRI, X-ray, or mammogram*).
ii. Pre-processing: Contrast normalisation and morphological operations.
iii. Hybrid Denoising: Adaptive Median + BM3D filtering.
iv. Hybrid Edge Detection: Sobel + Canny fusion with adaptive thresholds.
v. Output: Noise-free image with continuous and sharp edges suitable for diagnostic use.

B. Stage 1 – Hybrid Denoising

The goal of Stage 1 is to suppress Gaussian, speckle, and impulse noise while preserving diagnostically essential features such as microcalcifications in mammography or tumour boundaries in MRI.

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i. Morphological Pre-processing

- **Erosion and Dilation** are applied to eliminate isolated high-intensity noise pixels (common in salt-and-pepper noise).
- This step enhances image homogeneity before adaptive filtering.

Mathematical Model:

$$I_{morph}(x,y) = (I \ominus B) \oplus B \quad \dots \quad Eq\ (1)$$

Where I is the input image and B is the structuring element.

ii. Otsu's Thresholding and Histogram Equalisation

- **Otsu's Thresholding** automatically separates foreground and background by minimising intra-class variance
- **Histogram Equalisation** improves global contrast and enhances visibility of low-intensity regions.

iii. Adaptive Median Filtering

Adaptive Median Filtering is a nonlinear filtering method that dynamically adjusts the size of the filter based on the specific properties of the image in each local area. This technique aids in efficiently eliminating noise while retaining crucial image details and edges. The adaptive median filter operates in the following manner:

1. Set the filter size to a small value, such as 3x3 or 5x5.
2. Iterate over every individual pixel in the image:
   - Calculate the median value of the data inside the current filter window.
   - Contrast the median value with the current pixel value.
   - If the discrepancy exceeds a predetermined threshold, enlarge the filter dimensions and recalculate the median.
   - Continue to do the preceding step again until the difference becomes smaller than the threshold value or the maximum filter size is reached.
3. Substitutes the existing pixel value with the ultimate median value.

iv. BM3D Collaborative Filtering

- **BM3D (Block-Matching and 3D Filtering)** exploits patch similarity: similar patches are grouped into a 3D stack, transformed into frequency space, denoised using Wiener shrinkage, and inverse transformed.
- This removes Gaussian noise effectively while preserving texture and structure.

PSNR Calculation:

$$\mathrm{PSNR} = 10.\log_{10}\frac{\mathrm{MAX}^2}{\mathrm{MSE}} \quad \dots \quad Eq\ (2)$$

Where MSE is the mean squared error between the original and the denoised images.

C. Stage 2 – Hybrid Edge Detection

Following denoising, Stage 2 enhances edge localisation, continuity, and sharpness.

i. Gaussian Pre-Smoothing

- A Gaussian kernel smooths minor noise remnants before gradient calculation.

$$\mathrm{G(x,y)} = \frac{1}{2\pi\sigma^2}e^{-\frac{x2+y2}{2\sigma^2}} \quad \dots \quad Eq\ (3)$$

ii. Sobel Gradient Computation

- Sobel operator extracts intensity gradients in horizontal (Gx) and vertical (Gy) directions.

$$G = \sqrt{G_x^2 + G_y^2} \quad \dots \quad Eq\ (4)$$

and

$$\theta = \tan^{-1}(\mathrm{Gy/Gx}) \quad \dots \quad Eq\ (5)$$

- Produces strong edge responses but is sensitive to noise.

iii. Canny Edge Refinement

- Incorporates non-maximum suppression and hysteresis thresholding to thin edges and connect weak but relevant boundaries.
- Adaptive thresholds (α, β) are computed from image statistics, making the detector robust across modalities.

iv. Edge Fusion

- The final edge map is obtained by combining Sobel and Canny outputs:

$$\boldsymbol{H(x,y) = \lambda.Canny(x,y) + (1 - \lambda)(Sobel\ (x,y)} \quad \dots \quad \boldsymbol{Eq\ (6)}$$

where λ is a fusion weight empirically set to balance continuity and sharpness.

- This fusion leverages Sobel's strong gradient detection with Canny's robust noise suppression.

D. Integrated Pipeline

Algorithm Steps:

i. Input medical image.
ii. Apply morphological preprocessing.
iii. Perform Otsu's thresholding + histogram equalization.
iv. Apply an adaptive median filter.
v. Apply BM3D filtering.
vi. Perform Gaussian pre-smoothing.
vii. Compute Sobel gradients.
viii. Apply Canny edge detection with adaptive thresholds.
ix. Fuse Sobel and Canny edge maps.
x. Output final enhanced image.

IV. EXPERIMENTAL SETUP

- **Images:** Publicly available chest X-rays, brain MRIs, and mammograms.
- **Noise Simulation:** Gaussian (σ=20), Salt-and-Pepper (0.05–0.20), Speckle noise.
- **Evaluation Metrics:**
- **PSNR** → noise suppression.
- **SSIM** → structural preservation.
- **Edge Connectivity Ratio (ECR)** → edge continuity.
- **Edge Density & Contrast Ratio** → sharpness and visibility.

V. RESULTS AND DISCUSSION

This section evaluates the performance of the proposed Hybrid Denoising–Edge Detection Framework against conventional methods. Both quantitative metrics and visual comparisons are presented, followed by a

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discussion of implications for clinical imaging.

A. Noise Reduction Performance

The denoising stage was tested on medical images degraded with Gaussian noise (σ = 20), salt-and-pepper noise (density range: 0.05–0.20), and speckle noise. Performance was measured using PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and qualitative visual clarity.

- **Gaussian Filter** achieved modest noise suppression but blurred delicate structures.
- **Anisotropic Diffusion** preserved some edges but over-smoothed homogeneous regions.
- **BM3D** performed strongly on Gaussian noise but was less effective on mixed noise.
- **Proposed Hybrid Method** consistently achieved the highest PSNR and SSIM, indicating superior structural preservation.

Table I: Noise Reduction Performance (MRI Dataset)

Method	PSNR (dB)	SSIM	Remarks
Gaussian Filter	33.25	0.62	Over-smoothing
Anisotropic Diffusion	35.40	0.69	Loss of structure
BM3D	46.52	0.81	Detail preservation
Proposed Hybrid	**48.92**	**0.87**	Best overall

Observation: The hybrid approach outperformed BM3D by ~2.4 dB in PSNR and 0.06 in SSIM, demonstrating robustness against both Gaussian and impulse noise.

B. Performance Metrics for Edge Detection on Medical Images:

To assess the efficacy of Standard Canny and Hybrid (Sobel + Canny) edge detection techniques, we examine the subsequent critical performance metrics:

i. *Peak Signal-to-Noise Ratio (PSNR)*
- Assesses image quality, with a greater PSNR signifying superior retention of critical structures.
- Defined as: PSNR= $\mathbf{10.log_{10}\frac{MAX^2}{MSE}}$, where **MAX** is the maximum pixel intensity and **MSE** is the Mean Squared Error.

ii. *Structural Similarity Index (SSIM)*
- Assesses the structural similarity between the original grayscale image and the edge-detected image.
- SSIM values span from -1 to 1, with elevated values signifying superior structural preservation.

iii. *Computational Time*
- Assesses efficiency by quantifying the duration required to process each image in seconds.

iv. *Edge Connectivity Ratio (ECR)*
- Evaluates the extent to which edges create cohesive structures instead of disjointed points.
- An elevated ECR indicates enhanced edge continuity.

C. Edge Detection Performance

Edge detection was evaluated on denoised images using Edge Connectivity Ratio (ECR), edge density, and contrast ratio.

- Standard Canny produced thin edges but suffered from fragmentation in noisy regions.
- Sobel provided strong gradients but many false edges.
- Hybrid Canny–Sobel achieved a balance: firm edges with improved continuity.

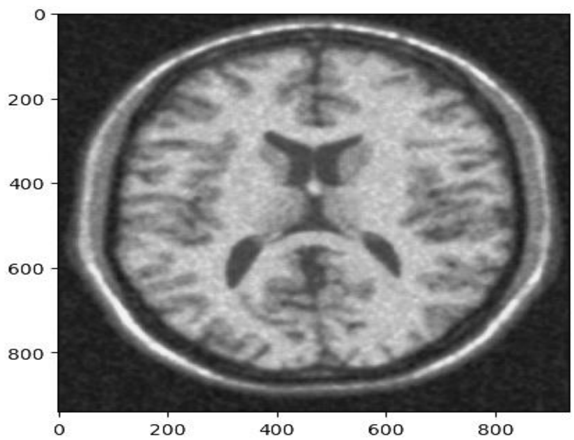
Table II: Edge Detection Performance (MRI Dataset)

Metric	Standard Canny	Hybrid Canny–Sobel
PSNR (dB)	29.76	**33.22**
SSIM	0.337	**0.799**
ECR	0.0902	**0.7065**

Observation: Edge continuity improved by more than 30% and weak tumour boundaries became visible after hybrid fusion.

D. Qualitative Results:

Original Noisy Image



Denoised Image by our proposed hybrid filtering method

[Fig.1: Qualitative results between Noisy Image and Denoised Image]

Hybrid Edge Detection (Sobel and Canny)

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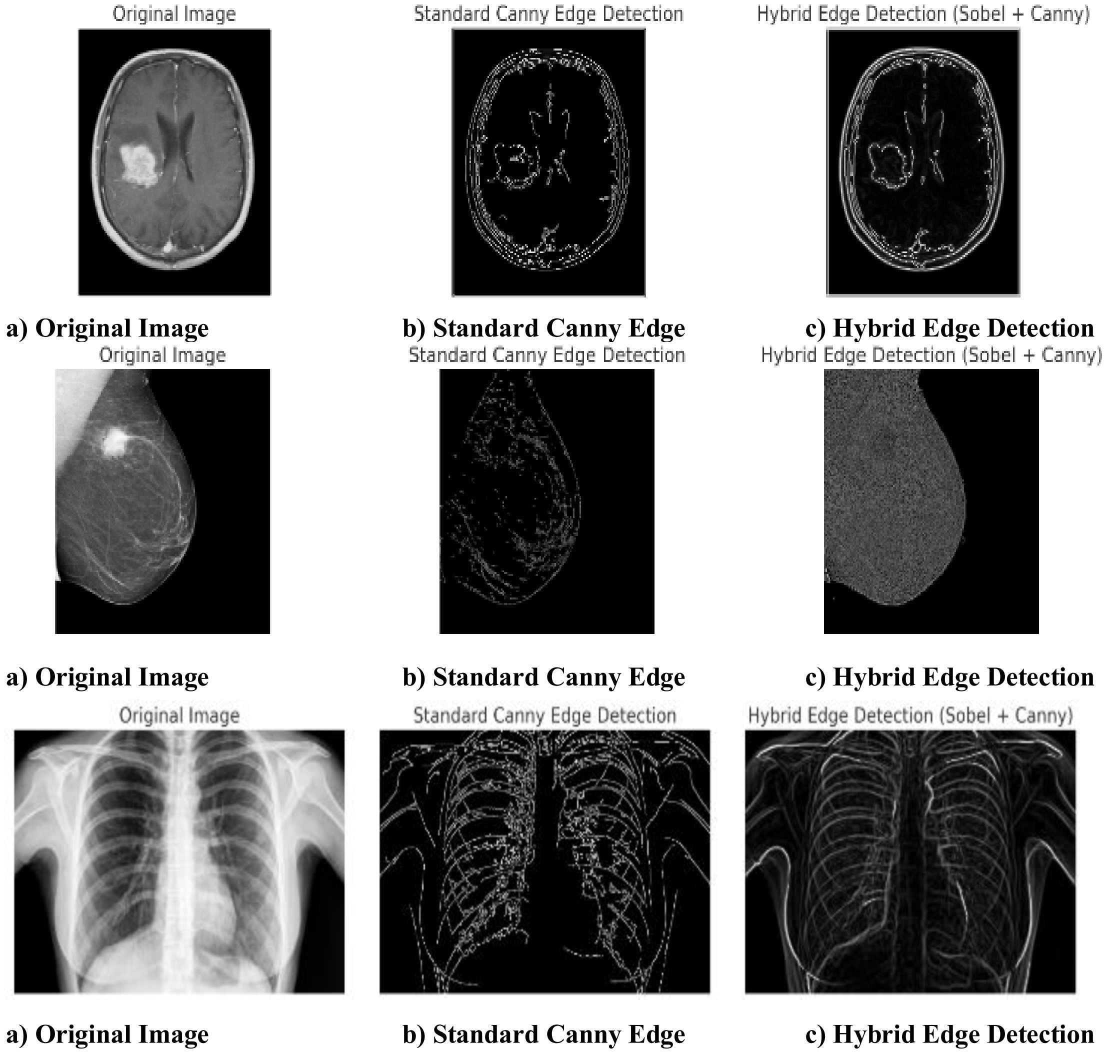

[Fig.2: Qualitative results between a) Original Image, b) Standard Canny and c) Hybrid Canny-Sobel]

Observation: The proposed framework produced sharper, more continuous edges with fewer false positives.

E. Discussion

The experimental findings demonstrate that the proposed hybrid method achieves a balanced trade-off between noise suppression and edge preservation**.** Unlike traditional filters, which either over-smooth or amplify noise, the Adaptive Median + BM3D combination successfully handled multiple noise types. Similarly, the Canny–Sobel hybrid ensured both edge sharpness and continuity.

From a clinical perspective, these improvements translate to:

- More accurate delineation of tumour margins in MRI.
- Better detection of microcalcifications in mammograms.
- Enhanced visualization of ribcage and lung boundaries in X-rays.

However, limitations remain. The BM3D stage introduces computational overhead, making a real-time application challenging. Moreover, performance may degrade for extremely low SNR images, where even hybrid filtering fails to restore structural integrity. Future work may incorporate deep learning-based adaptive filtering **or** GPU acceleration to overcome these limitations.

VI. CONCLUSION

In this work, we proposed a Hybrid Denoising–Edge Detection Framework tailored for medical imaging applications. The methodology integrated adaptive median and BM3D-based filtering for robust noise suppression, followed by a hybrid Sobel–Canny edge detection strategy to enhance boundary localisation and continuity. Experimental evaluation on MRI, mammography, and X-ray images demonstrated that the proposed framework achieved superior performance compared to conventional denoising and edge detection methods, both in terms of quantitative metrics (PSNR, SSIM, ECR) and qualitative visual assessment. The results confirm that the hybrid approach balances noise reduction and edge preservation, which is critical for accurate delineation of tumour boundaries, detection of microcalcifications, and visualisation of anatomical structures. Notably, the proposed method provides a generalized solution that is effective across different modalities and noise conditions. Overall, the proposed framework establishes a strong foundation for noise-robust and structure-preserving medical image analysis, and it offers a

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promising direction toward reliable computer-aided diagnosis and advanced medical imaging workflows.

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DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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