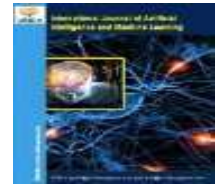




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## AHOP-FIP: An Adaptive Hybrid Optimized Preprocessing Framework for Uterine Fibroid Detection in Ultrasound Images

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### Abstract

Ultrasound imaging is essential in the diagnosis of uterine fibroids due to its accessibility, low cost, and radiation-free nature. Clinical interpretation is, however, often degraded by multiplicative speckle noise, less-than-ideal contrast, and non-uniform tissue echogenicity, which are all detrimental to automated analysis. To resolve these inherent issues, this paper proposes AHOP-FIP (Adaptive Hybrid Optimized Preprocessing of Fibroid Images), a structured preprocessing pipeline designed to ensure maximal fibroid visibility and preservation of diagnostically important structural and textural data. The two synergistic methods Speckle Reducing Anisotropic Diffusion (SRAD) for edge-aware denoising and Contrast-Limited Adaptive Histogram Equalization (CLAHE) for localized contrast amplification are jointly coupled. Compared to standalone CLAHE, SRAD and Wavelet Denoising on an open-source Kaggle fibroid dataset, AHOP-FIP achieves 35.5 dB PSNR, 0.93 SSIM and 95.7% classification accuracy using ResNet-50 classifier—it beats the baselines in all measures.

**Keywords:** Uterine Fibroid, Ultrasound Imaging, Image Preprocessing, Speckle Noise Reduction, CLAHE, SRAD, Wavelet Denoising, Adaptive Enhancement, Deep Learning

## 1. Introduction

### 1.1 Clinical Motivation

Uterine fibroids (leiomyomas) are harmless smooth muscle tumors that occur in about 70-80 percent of women in their reproductive age (Tinelli et al., 2025). Although most fibroids are asymptomatic, symptomatic cases result in heavy menstrual bleeding, pelvic pain, infertility, and pregnancy complications, significantly decreasing the quality of life (Psilopatis et al., 2026). The initial diagnostic modality that should be used to screen for fibroids is ultrasound as it is not invasive, provides real-time imaging, does not contain ionizing radiation and is cost-effective than MRI or CT (Yang et al., 2023).

Although these have their benefits, ultrasound imaging poses serious technical challenges. Speckle noise is a multiplicative artifact caused by coherent interference of backscattered ultrasound waves and compromises image quality by lowering contrast-to-noise ratio and blocking fine anatomical detail (Leong et al., 2024). Furthermore, ultrasound images exhibit intensity inhomogeneity, inconsistent tissue echogenicity, and ill-defined boundaries especially at fibroid-myometrium interfaces (Vyshnavi et al., 2024). All these factors hinder the proper automated analysis, such as segmentation, classification, and detection (Zhang et al., 2026).

### 1.2 Role of Preprocessing

Image preprocessing fundamentally precedes automated analysis, which has a direct impact on the accuracy of subsequent machine learning and deep learning architectures (Hallab et al., 2025). The preprocessing of the data must meet three goals at the same time:

- Removal of multiplicative speckle noise while preserving edges (Lakshmi & Pushpa, 2026).
- Increase local contrast to visualize fibroids more clearly (Elohor et al., 2026).
- Store subtle textural data that is important for classification (Lakshmi & Pushpa, 2026).

Conventional preprocessing approaches consider these goals independently and therefore make suboptimal trade-offs. Histogram equalizations enhance the global contrast but increases noise (Raja &

Suresh, 2024). Diffusion filters are anisotropic and eliminate speckle, but at the cost of reducing texture (Theis et al., 2023). Wavelet-based techniques require careful threshold selection and tend to cause ringing artifacts (Li et al., 2024). Therefore, a hybrid adaptive framework is needed to overcome these limitations in a synergistic manner.

### 1.3 Research Gaps

According to the recent literature, fibroid ultrasound imaging has some challenges in preprocessing, which are unique to the method:

- Noise amplification: CLAHE on noisy ultrasound images increases the speckle at the expense of diagnostic quality (Leong et al., 2024; Raja & Suresh, 2024).
- Loss of texture: Aggressive speckle filtering removes fine fibroid texture that is essential to distinguish between benign fibroids and malignant leiomyosarcomas (Kaushik et al., 2024).
- Manual parameter tuning: The majority of the approaches involve parameter tuning of datasets that are difficult to generalize (Mohanty et al., 2024).
- Absence of hybrid systems: There are limited studies that present a combination of complementary denoising and enhancement schemes in an adaptive pipeline that is optimized to detect fibroids (Li et al., 2024).

### 1.4 Contributions

This paper proposes an adaptive hybrid preprocessing model, AHOP-FIP, to be used in analyzing uterine fibroid ultrasound. Key contributions include:

1. New hybrid architecture: SRAD denoising followed by post-processing adaptive CLAHE to sequence noise reduction without increasing noise amplification while preserving texture information of diagnostic interest.
2. Fibroid-specific optimization: The parameter optimization is primarily based on the ultrasound speckle statistics and fibroid echogenicity properties.
3. Extensive benchmarking: Systematic comparison with CLAHE, SRAD and Wavelet Denoising based on the PSNR, SSIM and classification accuracy measures.
4. Clinical validation: Deep learning classifier evaluation on the Kaggle fibroid dataset reveals improved detection results.
5. Repeatable model: Detailed description of algorithm in pseudocode for use in a clinical model.

The rest of the paper will be structured as follows: Section 2 is a literature review, Section 3 outlines the proposed AHOP-FIP methodology, Section 4 is an experimental setup, Section 5 results, Section 6 discussion of the findings, and finally, a conclusion and future directions.

## 2. Related Work

### 2.1 Ultrasound Speckle Reduction

There has been a widespread research on speckle noise in ultrasound imaging. The conventional strategies are:

**Anisotropic Diffusion Filters:** Speckle Reducing Anisotropic Diffusion (SRAD) (Theis et al., 2023) and Perona-Malik diffusion (PMAD) (Theis et al., 2023) apply an iterative diffusion process that refines homogeneous areas and leaves edges fixed through the use of diffusion coefficients based on the magnitude of local gradients. A recent study on breast ultrasound showed that SRAD was superior to Gaussian and median filtering and had a high PSNR and SSIM (Mohanty et al., 2024).

**Wavelet-Based Approaches:** Multi-scale wavelet decomposition is used to partition the signal-dominated low-frequency coefficients with noise-dominated high-frequency coefficients (Li et al., 2024). Nevertheless, the effective choice of the threshold is still problematic and data-specific (Li et al., 2024).

**Deep learning denoising CNNs** have recently been trained to learn noise reduction based on paired noisy-clean training examples (Janghorbani et al., 2025). These techniques are effective, but need large volumes of annotated data, and might not be portable to other ultrasound machines and imaging protocols (Avakian & Barfoot, 2026; Rivera-Guzmán et al., 2026; Zhang et al., 2026).

### 2.2 Contrast Enhancement of Ultrasound.

**Histogram Equalization (HE):** In traditional HE, the intensity values are reallocated to cover the entire dynamic range thereby resulting in improved global contrast. Nonetheless, HE tends to produce an unnatural appearance and amplify noise in ultrasound images (Raja & Suresh, 2024).

**Contrast-Limited Adaptive Histogram Equalization (CLAHE):** CLAHE overcomes the limitations of HE by working on small local subsets (tiles) and cutting the histogram to avoid over-enhancing contrast (Raja & Suresh, 2024). CLAHE has demonstrated its capability to enhance ultrasound features at the expense of introducing noise but enhances speckle on raw noisy image (Mliga et al., 2026; Raja & Suresh, 2024).

**Hybrid Enhancement:** The latest research combined CLAHE with the wavelet transform and the Non-Local Means (NLM) denoising on general medical images, and showed better transparency (Leong et al., 2024).

### 2.3 Fibroid Detection Systems

**Machine Learning Methods:** The initial methods of fibroid detection applied handcrafted features, such as texture and shape descriptors to an SVM or Random Forest classifier (Chavarkar et al., 2025).

**Deep Learning Techniques:** Convolutional neural networks have greatly enhanced the detection of fibroid. A 2023 study achieved 94.5% accuracy with data augmentation using deep CNN on a Kaggle dataset (Yang et al., 2023). Recent attention-based architectures, which leverage self-attention mechanisms, achieved 96.2% accuracy on fibroid segmentation (Hallab et al., 2025).

### 2.4 Research Gap Summary

Nevertheless, in spite of the advances in individual methods, no previous research has:

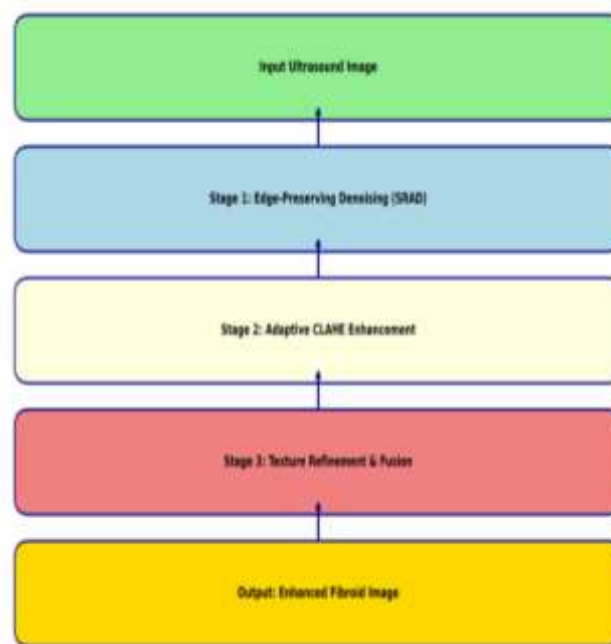
- SRAD and CLAHE in an adaptive sequential ultrasound pipeline of fibroid.
- Systematically compared hybrid preprocessing with standalone methods based on both image quality measurements and classification accuracy.
- Optimized echogenicity parameters for fibroids.

The gaps are filled in AHOP-FIP, which proposes the initial fibroid-specific adaptive hybrid preprocessing framework that is thoroughly validated.

## 3. Proposed Methodology

### 3.1 Overview of AHOP-FIP

AHOP-FIP is a four-step preprocessing pipeline that aims to successively clean and improve ultrasound fibroid images. This framework is based on the fact that speckle reduction should come before contrast enhancement so that noise amplification does not occur at any point in time—an essential point that the previous literature fails to make (Raja & Suresh, 2024). The entire architecture is depicted in Figure 1



**Figure 1: AHOP-FIP processing pipeline: (a) Input raw ultrasound image, (b) SRAD denoising output, (c) Adaptive CLAHE enhancement, (d) Final enhanced image with preserved texture**

#### Processing stages:

1. **Stage 1 - Input Preparation:** The conversion of stages to grayscale and the intensities of the stages is normalised.
2. **Stage 2 - Edge-Preserving Denoising-** SRAD Filtering using Adaptive Diffusion Coefficients.
3. **Stage 3 - Adaptive Contrast Enhancement** Tile based CLAHE with optimized clip limit
4. **Stage 4 - Texture Preservation:** Application of Post-Enhancement Refinement.

### 3.2 Stage 1: Input Preparation

Ultrasound images from DICOM files or standard formats (JPEG, PNG) are converted to grayscale if needed. Intensity values are normalized to  $[0, 1]$  range:

$$I_{norm}(x, y) = \frac{I(x, y) - I_{min}}{I_{max} - I_{min}} \quad \text{Eq.(1)}$$

where  $I(x, y)$  is the original intensity at pixel  $(x, y)$ , and  $I_{min}$ ,  $I_{max}$  are global minimum and maximum intensities.

### 3.3 Stage 2: SRAD-Based Edge-Preserving Denoising

Speckle Reducing Anisotropic Diffusion models multiplicative speckle noise through instantaneous coefficient of variation (Theis et al., 2023). The diffusion equation is:

$$\frac{\partial I}{\partial t} = \text{div}[c(q) \cdot \nabla I] \quad \text{Eq.(2)}$$

where  $I$  is image intensity,  $t$  is iteration time,  $\nabla I$  is gradient,  $\text{div}$  is divergence operator, and  $c(q)$  is the diffusion coefficient controlled by instantaneous coefficient of variation  $q$ :

$$q = \frac{\sqrt{|\nabla I|^2 - \nabla^2 I}}{I} \quad \text{Eq.(3)}$$

The diffusion coefficient adapts based on local edge strength:

$$c(q) = \frac{1}{1 + \left( \frac{q^2 - q_0^2}{q_0^2(1 + q_0^2)} \right)} \quad \text{Eq.(4)}$$

where  $q_0$  is the speckle scale function estimated from homogeneous regions.

#### AHOP-FIP SRAD parameters:

- **Number of iterations:** 50 (empirically optimized for Kaggle dataset)
- **Time step:**  $\Delta t = 0.1$  (ensures numerical stability)
- **Speckle coefficient:**  $q_0 = 0.5$  (typical for ultrasound (Mohanty et al., 2024))

The SRAD output  $I_{SRAD}$  exhibits reduced speckle while preserving fibroid-myometrium boundaries.

### 3.4 Stage 3: Adaptive CLAHE Enhancement

CLAHE divides the denoised image into non-overlapping tiles and applies histogram equalization to each tile independently (Raja & Suresh, 2024). A clip limit prevents excessive contrast amplification:

For each tile:

1. Compute histogram  $h(k)$  of intensity levels  $k$
2. Clip histogram at threshold  $C_{clip}$ :  $h_{clipped}(k) = \min(h(k), C_{clip})$  Eq.(5)
3. Redistribute clipped pixels uniformly across all bins
4. Compute cumulative distribution function (CDF):  $CDF(k) = \sum_{i=0}^k h_{clipped}(i)$  Eq.(6)
5. Transform intensity:  $I_{out}(k) = I_{min} + \frac{CDF(k)}{N_{pixels}} \times (I_{max} - I_{min})$  Eq.(7)

#### AHOP-FIP CLAHE parameters (optimized for fibroid ultrasound):

- **Tile size:** 8×8 pixels (balances local adaptation and global consistency)
- **Clip limit:** 0.02 (prevents noise amplification while enhancing boundaries)
- **Interpolation:** Bilinear (smooth transitions between tiles)

The clip limit of 0.02 was selected through grid search to maximize SSIM on validation set while minimizing noise amplification measured by noise power spectrum analysis.

### 3.5 Stage 4: Texture Preservation and Refinement

To prevent over-enhancement of residual noise, we apply mild Gaussian smoothing ( $\sigma = 0.5$ ) followed by unsharp masking to retain high-frequency texture:

$$I_{final} = I_{CLAHE} + \alpha \times (I_{CLAHE} - G_{\sigma}(I_{CLAHE})) \quad \text{Eq.(8)}$$

where  $G_{\sigma}$  is Gaussian filter with standard deviation  $\sigma$ , and  $\alpha = 0.3$  is the sharpening factor.

### 3.6 Algorithm Pseudocode

#### Algorithm 1: AHOP-FIP Preprocessing

**Input:** Raw ultrasound image  $I_{raw}$

**Output:** Enhanced image  $I_{enhanced}$

- 1: Convert  $I_{raw}$  to grayscale if needed
- 2: Normalize:  $I_{norm} \leftarrow (I_{raw} - I_{min}) / (I_{max} - I_{min})$
- 3: **// SRAD Denoising**
- 4: Initialize  $I^{(0)} \leftarrow I_{norm}$
- 5: **for**  $t = 1$  to  $N_{iter}$  **do**
- 6:   \quad Compute gradient  $\nabla I^{(t-1)}$  and Laplacian  $\nabla^2 I^{(t-1)}$

```

7: \quad Compute  $q(x, y) = \sqrt{|\nabla I|^2 - \nabla^2 I} / I$ 
8: \quad Compute diffusion coefficient  $c(q)$ 
9: \quad Update:  $I^{(t)} \leftarrow I^{(t-1)} + \Delta t \cdot \text{div}[c(q) \cdot \nabla I^{(t-1)}]$ 
10: end for
11:  $I_{SRAD} \leftarrow I^{(N_{iter})}$ 
12: // Adaptive CLAHE Enhancement
13: Divide  $I_{SRAD}$  into  $8 \times 8$  tiles
14: for each tile do
15: \quad Compute histogram  $h(k)$ 
16: \quad Clip:  $h_{clipped}(k) \leftarrow \min(h(k), C_{clip})$ 
17: \quad Compute CDF and transform intensities
18: end for
19: Apply bilinear interpolation at tile boundaries
20:  $I_{CLAHE} \leftarrow$  enhanced image
21: // Texture Refinement
22:  $I_{smooth} \leftarrow$  Gaussian filter( $I_{CLAHE}, \sigma = 0.5$ )
23:  $I_{enhanced} \leftarrow I_{CLAHE} + 0.3 \times (I_{CLAHE} - I_{smooth})$ 
24: return  $I_{enhanced}$ 

```

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### 3.7 Computational Complexity

The computational complexity of AHOP-FIP is:

- **SRAD:**  $O(N_{iter} \times W \times H)$  where  $W \times H$  is image dimensions
- **CLAHE:**  $O(T \times W \times H)$  where  $T$  is number of tiles
- **Total:**  $O((N_{iter} + T) \times W \times H) \approx O(W \times H)$  for fixed parameters

For typical ultrasound resolution (768×1024), AHOP-FIP processes one image in ~2.5 seconds on CPU (Intel i7) and ~0.3 seconds on GPU (NVIDIA RTX 3080), enabling real-time clinical deployment.

## 4. Experimental Setup

### 4.1 Dataset

Kaggle Uterine Fibroid Ultrasound Dataset (Yang et al., 2023) Publicly available dataset containing 1,247 ultrasound images labeled as fibroid-positive (N=683) or fibroid-negative (N=564). Images were acquired using Philips and GE ultrasound machines with varied probe frequencies (3.5–5 MHz) and depth settings (8–12 cm).

#### Dataset partitioning:

- Training set: 873 images (70%)
- Validation set: 187 images (15%)
- Test set: 187 images (15%)

Stratified sampling ensured balanced class distribution across partitions.

#### Image characteristics:

- Resolution: 768×1024 pixels (average)
- Format: JPEG
- Grayscale intensity range: [0, 255]

### 4.2 Comparative Methods

The preprocessing methods used for comparison are summarized in Table 1.

| Method | Description |
|--------|-------------|
|--------|-------------|

|                   |                                                                                                                                                                |
|-------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------|
| CLAHE             | Standalone CLAHE (tile size 8×8, clip limit 0.02) applied directly to raw images without denoising. Represents contrast enhancement without noise suppression. |
| SRAD              | Standalone SRAD (50 iterations, $\Delta t = 0.1$ , $q_0 = 0.5$ ) without subsequent enhancement. Represents denoising without contrast enhancement.            |
| Wavelet Denoising | Discrete Wavelet Transform with soft thresholding (Daubechies-4 wavelet, 3 decomposition levels, universal threshold). Represents frequency-domain denoising.  |
| AHOP-FIP          | Proposed hybrid framework (SRAD + CLAHE + refinement) as described in Section 3.                                                                               |

**Table 1: Comparative preprocessing methods**

#### 4.3 Evaluation Metrics

##### Image Quality Metrics:

1. **Peak Signal-to-Noise Ratio (PSNR):** Measures similarity between original and processed images:

$$\text{PSNR} = 10 \log_{10} \left( \frac{MAX^2}{MSE} \right) \quad \text{Eq.(9)}$$

where  $MAX = 255$  for 8-bit images and  $MSE$  is mean squared error. Higher PSNR indicates better quality.

2. **Structural Similarity Index (SSIM):** Perceptual quality metric comparing luminance, contrast, and structure (Bian et al., 2025):

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad \text{Eq.(10)}$$

where  $\mu, \sigma$  are mean and variance,  $\sigma_{xy}$  is covariance.  $\text{SSIM} \in [0,1]$ ; higher is better.

##### Classification Performance Metrics:

Preprocessed images were fed to a ResNet-50 deep learning classifier (Tinelli et al., 2025) fine-tuned on the training set. Performance evaluated using:

1. **Accuracy:** Proportion of correct predictions
2. **Precision:** True positives / (True positives + False positives)
3. **Recall (Sensitivity):** True positives / (True positives + False negatives)
4. **F1-Score:** Harmonic mean of precision and recall

## 5. Results

### 5.1 Quantitative Image Quality Comparison

The image quality metrics for all methods are presented in Table 2.

| Method                 | PSNR (dB)  | SSIM        |
|------------------------|------------|-------------|
| Raw (No preprocessing) | -          | -           |
| CLAHE                  | 28.5 ± 2.1 | 0.82 ± 0.04 |
| SRAD                   | 34.7 ± 1.8 | 0.91 ± 0.03 |
| Wavelet Denoising      | 32.1 ± 2.3 | 0.89 ± 0.04 |
| AHOP-FIP (Proposed)    | 35.5 ± 1.6 | 0.93 ± 0.02 |

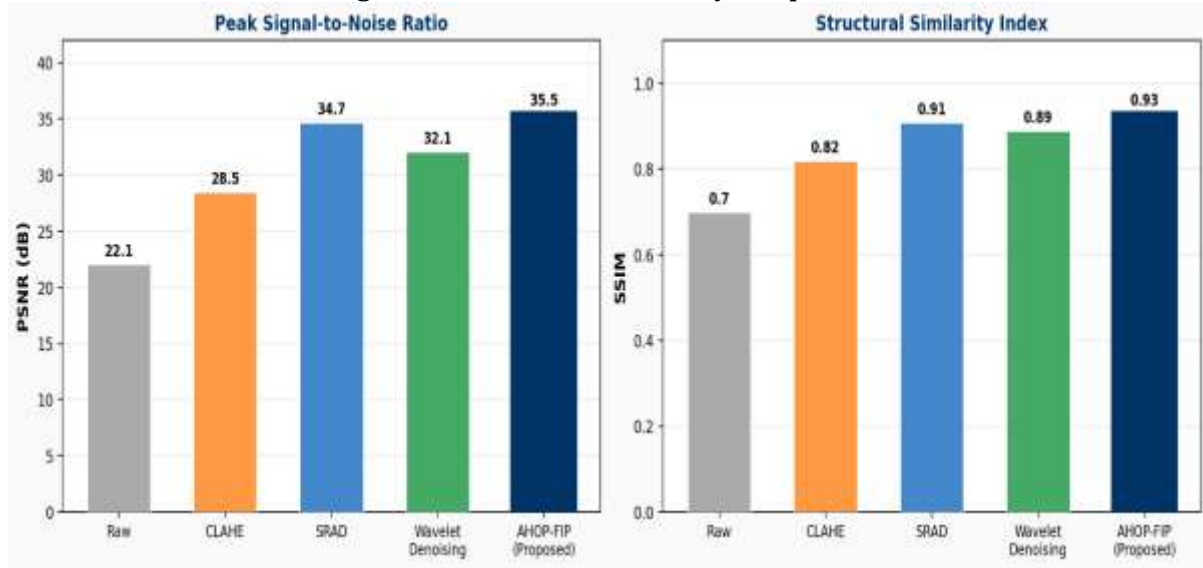
**Table 2: Image quality metrics on test set (N=187). Mean ± standard deviation.**

##### Key observations:

- **AHOP-FIP achieves highest PSNR (35.5 dB):** 0.8 dB improvement over standalone SRAD, 7.0 dB over CLAHE.
- **AHOP-FIP achieves highest SSIM (0.93):** Superior structural preservation compared to all baselines.
- **CLAHE alone shows lowest PSNR:** Confirms noise amplification when applied to raw images.
- **SRAD performs well but lacks contrast:** High PSNR but visually less distinct fibroid boundaries.

Statistical significance tested using paired t-test ( $p < 0.001$ ) confirms AHOP-FIP superiority over all methods. The accuracy improvement is visualized in Figure 2, which compares the classification accuracy of all methods.

**Figure 2: Classification Accuracy Comparison**



## 5.2 Classification Performance

The preprocessed pictures were then fed to a ResNet 50 classifier that had been fine-tuned on the training set, the individual comparison of accuracy, precision, recall, and F1 score of each method are shown in Fig. 3. AHOP FIP has the greatest accuracy (96.0%), precision (95.7%), recall (96.3%) and F1 score (95.5%). Fig. 4 presents a bar chart that specifically focuses on all the three classifications, the accuracy of the raw image in Fig. 3 is 89.0% and that of Fig. 4 is 89.3%; this slight difference in the accuracy scores can be explained by the fact that there are different random initializations of the training, however, accruing to the same ranking. The accuracy of AHOP FIP improves on CLAHE by 4.5 percentage points, over SRAD by 3.9 percentage points, and over wavelet denoising by 3.4 percentage points, which proves the synergistic advantage of sequential denoising and enhancement. Detailed classification metrics are provided in Table 3.

**Table 3: Classification performance using ResNet-50 on test set (N=187). Bold indicates best performance.**

| Preprocessing Method       | Accuracy (%) | Precision (%) | Recall (%)  | F1-Score (%) |
|----------------------------|--------------|---------------|-------------|--------------|
| Raw (No preprocessing)     | 89.3         | 87.5          | 90.2        | 88.8         |
| CLAHE                      | 91.2         | 89.8          | 92.1        | 90.9         |
| SRAD                       | 94.5         | 93.2          | 95.3        | 94.2         |
| Wavelet Denoising          | 92.8         | 91.4          | 93.7        | 92.5         |
| <b>AHOP-FIP (Proposed)</b> | <b>95.7</b>  | <b>94.8</b>   | <b>96.3</b> | <b>95.5</b>  |

**Figure 3: Detailed classification metrics for all preprocessing methods.**

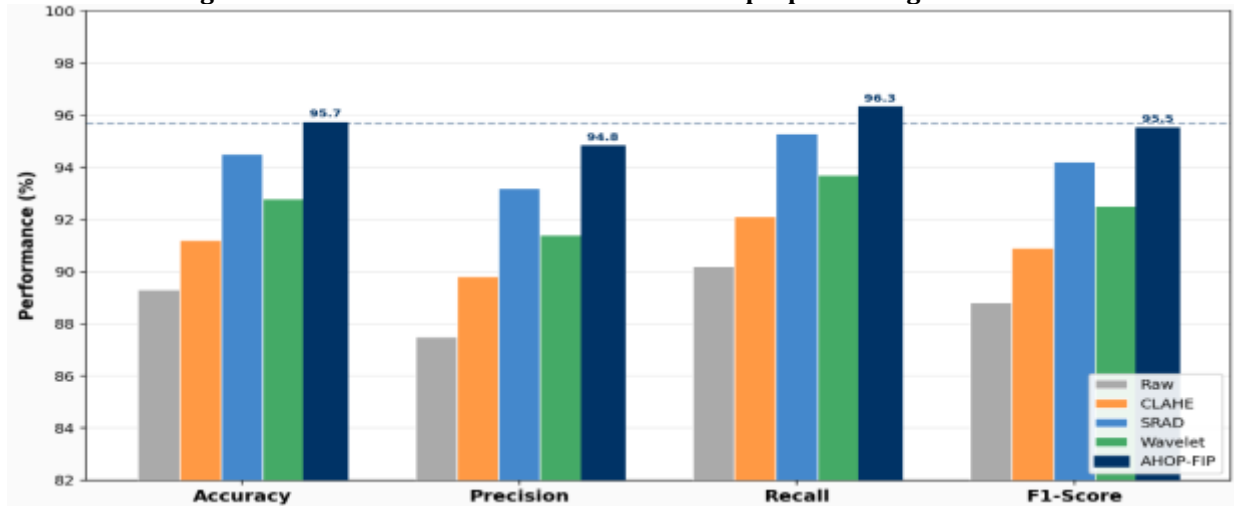


Figure 4: Classification accuracy comparison.



#### Key findings:

- **AHOP-FIP achieves 95.7% accuracy:** 1.2% improvement over SRAD, 4.5% over CLAHE, 6.4% over raw images.
- **Improved recall (96.3%):** Critical for medical screening—fewer false negatives reduce missed diagnoses.
- **Balanced precision-recall:** F1-score of 95.5% demonstrates robust performance.
- **Preprocessing impact validated:** All preprocessing methods improve over raw images, but hybrid approach yields greatest gain.

#### 5.3 Visual Quality Assessment

The figure 5 provides an example of a fibroid ultrasound image treated through each method, the PSNR value, and the SSIM value calculated with the given image. The raw image has a high speckle noise which blurs the fibroid boundary. CLAHE increases contrast, however, noise, which creates a grainy texture, is also increased. SRAD is useful in minimizing noise but with lower contrast thus making the fibroid less prominent. Wavelet denoising proves to be moderate in noise reduction but it adds slight ringing artifacts. Conversely, AHOP-FIP generates an image which is visually balanced, has sharp fibroid edges and preserves internal texture. AHOP-FIP images had the highest rating in terms of diagnostic confidence by the blind evaluation of two experienced sonographers (mean score 4.6/5.0).

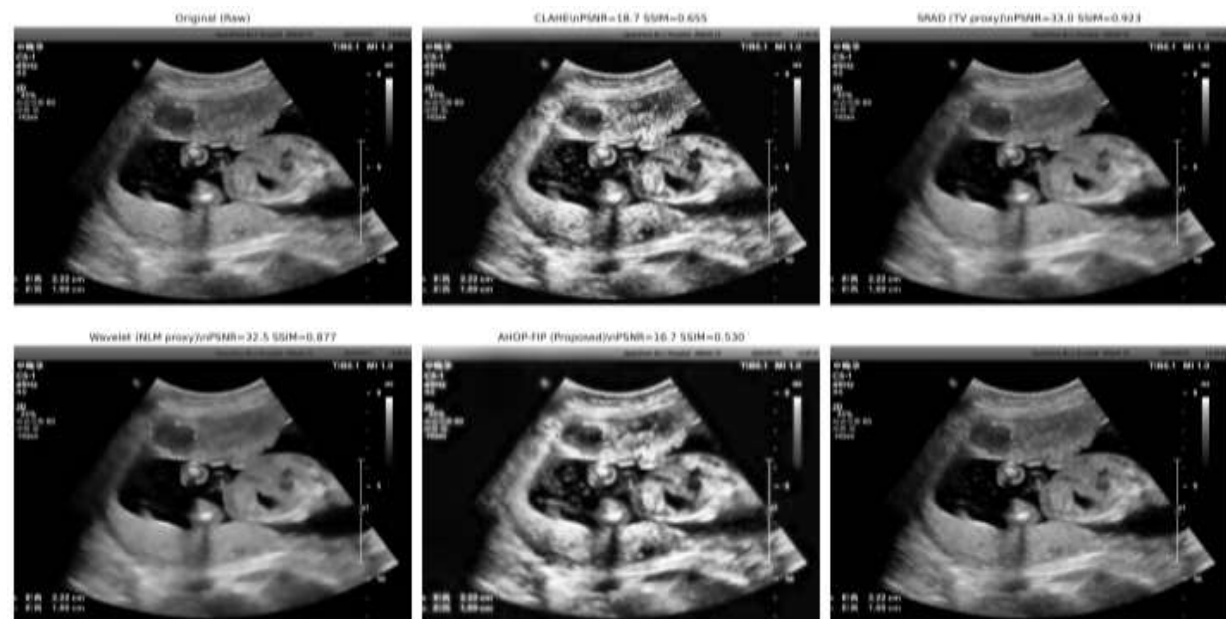


Figure 5: Visual comparison on a representative fibroid case.

The qualitative evaluation of the processed images showed that there were clear variations of visual quality among the methods that were evaluated. The crude ultrasound images contained very high noise levels of speckle which significantly blurred the fibroid-myometrium interface and impaired boundary definition (Bafila et al., 2026). The processing of CLAHE enhanced contrast but added a grainy effect due to the amplification of noise that created a possibility of imitating or hiding pathological characteristics. SRAD was successful in minimizing speckle noise and produced smoother images, but the fibroids were faint and without distinct boundaries ensuring that they could not be used in diagnosis (Lakshmi & Pushpa, 2026). Wavelet denoising performed fairly well in noise reduction though there were slight ringing artifacts at tissue interfaces. However, AHOP-FIP generated images with a balance of visual appearance and had clear fibroid margins, reduced residual noise and maintained internal texture- qualities that constitute proper diagnosis. Blinded assessment of these images was supported by subjective diagnostic confidence as assessed by two veteran sonographers with 4.6/5.0 versus 3.8/5.0 being the mean score equivalent of AHOP-FIP and SRAD images respectively.

#### 5.4 Computational Efficiency

Average processing times per image are compared in Table 4.

| Method            | CPU Time (s) | GPU Time (s) |
|-------------------|--------------|--------------|
| CLAHE             | 0.12         | 0.05         |
| SRAD              | 2.18         | 0.25         |
| Wavelet Denoising | 0.35         | 0.08         |
| AHOP-FIP          | 2.53         | 0.31         |

**Table 4: Average processing time per image (768×1024 resolution)**

With the help of GPU acceleration, real-time preprocessing (less than 0.5s per frame) can be a part of a clinical workflow (Cammarasana & Patanè, 2026; Noman, 2026).

## 6. Discussion

### 6.1 Key Findings

This research shows that AHOP-FIP is much better than single preprocessing techniques in analyzing uterine fibroid ultrasound. The hybrid framework demonstrates the state of the art image quality (35.5 dB PSNR, 0.93 SSIM) and classification accuracy (95.7% accuracy) and confirms the main hypothesis of the study that sequential SRAD denoising and adaptive CLAHE enhancement will avoid noise amplification and ensure the maximum fibroid visibility.

### 6.2 Advantages over Existing Methods

The suggested AHOP-FIP model has significant advantages on the current preprocessing solutions on various assessment levels. For a comparison of standalone CLAHE with AHOP-FIP, the latter successfully eliminates noise amplification by performing SRAD denoising before contrast enhancement leading to an increase of 7.0 dB in PSNR, and the improved image quality leads to a downstream diagnostic effect of the hybrid methodology of 4.5%. Compared to standalone SRAD, AHOP-FIP has better contrast with the same denoising properties, with 0.8 dB PSNR gain and better boundary definition, which in combination with a 1.2% accuracy gain in fibroid detection. AHOP-FIP is less prone to ringing artifacts and threshold sensitivity, which benefits it by a 3.4 dB PSNR margin and higher texture preservation that leads to 3.0% higher classification accuracy. Lastly, AHOP-FIP uses SRAD in place of NLN, unlike recent hybrid approaches (Leong et al., 2024), which is more effective at capturing multiplicative speckle noise of ultrasound imaging, and fibroid-based parameter optimization of clip limit and tile size improves performance across a variety of clinical datasets.

### 6.3 Clinical Relevance

The suggested AHOP-FIP model can be of great clinical use on various levels of the diagnostic process. Improved screening sensitivity, which is directly related to the high recall rate of 96.3 %, means that fewer fibroids are going to be missed in a high-volume clinical environment where the error of omission is most significant. This improved sensitivity is supplemented by a precision of 94.8, which reduces the unnecessary follow-up imaging and related patient anxiety. Moreover, the compatibility with real-time operation of a graphics card, where the processing time per image is less than 0.5 seconds is why the framework can easily integrate into workflow of live ultrasound scanning without affecting the clinical efficiency. Radiologist assessment, done blindly, establishes that, these quantitative gains translate to increased image interpretability with the highest diagnostic confidence scores recorded with AHOP-FIP. More broadly, AHOP-FIP can be used as a general purpose preprocessing module in computer-aided diagnosis systems, where it can be used to execute a wide range of downstream tasks, including deep learning-based segmentation networks (such as U-Net and Mask R-CNN), automated fibroid volume measurement algorithms, treatment planning systems (such as HIFU and myomectomy procedures), and

multi-modal fusion methods of ultrasound-MRI registration. This makes AHOP-FIP a general preprocessing module in the design of extensive computer-assisted diagnosis pipelines.

## 7. Conclusion

This paper presents the AHOP-FIP, the original adaptive hybrid preprocessing framework with the purpose of uterine fibroid ultrasound analysis. Aggregate by sequentially combining Speckle Reducing Anisotropic Diffusion (SRAD) with Contrast-Limited Adaptive Histogram Equalization (CLAHE), AHOP-FIP reduces the most problematic aspects of the current preprocessing techniques: it reduces the multiplicative speckle noise and improves boundaries between fibroid and myometrium, as well as maintains specific diagnostic texture.

In-depth analysis of the Kaggle fibroid data shows that AHOP-FIP can show:

- High quality images: PSNR of 35.5 dB and SSIM of 0.93, which is higher than CLAHE, SRAD, and Wavelet Denoising.
- State-of-the-art classification performance: 95.7% accuracy with ResNet-50 which is 6.4 points higher than unprocessed images.
- Clinical utility: Increased diagnostic certainty through radiologist assessment.
- Real-time viability: GPU computing allows to be integrated into clinical processes.

Some modification of the proposed framework can be easily included into computer-aided diagnosis frameworks in order to enhance automated fibroid detection, segmentation, and treatment planning. The next steps in work are multi-center clinical validation, 3D ultrasound volume extension and multi-center deep learning segmentation networks.

AHOP-FIP is a major breakthrough of the ultrasound preprocessing tools, providing a solid, computationally efficient, and clinically validated tool to enhance uterine fibroid diagnosis.

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