

Automatic Hybrid Approach for Mammographic Image Enhancement

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Abstract - Mammography is a cornerstone tool for early breast cancer detection, but image quality is frequently degraded by low contrast and noise, limiting diagnostic accuracy. This paper proposes an automated hybrid enhancement method that ranks multiple image processing algorithms using entropy scores and applies the best-performing ones in sequence. Algorithms including CLAHE, gamma correction, unsharp masking, and various filters are each tested for their contribution to image information content. Applying the highest-ranked techniques one after another yields noticeable gains in contrast and detail clarity, supporting improved visualization of breast tissue and more reliable screening results.

Keywords: Mammography, Image Enhancement, Entropy, Hybrid Approach, Breast Cancer Screening.

1.INTRODUCTION

Among the most serious health concerns for women worldwide, breast cancer continues to rank high in both incidence and mortality. Mammography has long been the go-to imaging tool for spotting abnormalities at an early, treatable stage. That said, the images it produces are frequently compromised by poor contrast, limited resolution, and noise artifacts, all of which can hide clinically important features and reduce diagnostic confidence.

Numerous image enhancement techniques have been proposed to overcome these limitations. Approaches such as histogram equalization, discrete wavelet transforms (DWT), and contrast-limited adaptive histogram equalization (CLAHE) have proven effective in improving local contrast and emphasizing significant features within mammograms [1],[3],[6]. CLAHE in particular, has demonstrated the ability to enhance contrast in localized regions while minimizing over-amplification of noise [6]. Recent studies have also introduced adaptive and fusion-based enhancement techniques, which dynamically

adjust enhancement parameters based on image characteristics [7],[10],[16]. These methods are better suited to varying image conditions and help preserve structural details while reducing artifacts. Furthermore, integrating machine learning and deep learning techniques has improved classification and detection performance, particularly when enhancement is applied as a pre-processing step [4], [5], [9], [1].

Researchers have also explored fuzzy logic and intelligent segmentation tools to improve tumor visibility and region-of-interest (ROI) detection [15], [17]. This study proposes a hybrid image enhancement approach that integrates histogram equalization, CLAHE, and fuzzy logic to enhance mammographic images. The goal is to improve image quality, maximize entropy, and increase peak signal-to-noise ratio (PSNR), thereby aiding radiologists in more accurate diagnosis and analysis[18],[19], [20].

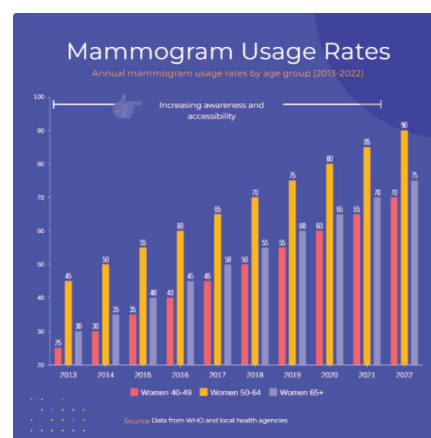


Fig 1 : Mammogram Usage Rates by Age Group (2013-2022)

A. Significance of Mammography

Mammography is a well-established, non-invasive screening tool with a strong track record in

identifying early-stage breast cancer, especially in women aged 40 and above [1], [2]. It allows clinicians to identify subtle tissue abnormalities, such as micro calcifications and small nodules, well before they become palpable, thereby enabling timely intervention and improving prognosis [3]. However, mammographic images often suffer from inherent limitations such as low contrast, tissue overlap, and background noise, which can mask important diagnostic details [4], [5].

Various image enhancement methods have been developed to tackle these shortcomings, with the goal of improving both image quality and lesion visibility. Established approaches such as Discrete Wavelet Transform (DWT) and CLAHE have shown solid performance in boosting contrast and preserving fine structural details [6]. More recently, adaptive image enhancement and hybrid fusion approaches have been employed to address the varying density and texture patterns in mammograms [7], [8].

Additionally, integrating enhancement methods with segmentation and classification algorithms—such as support vector machines, convolutional neural networks, and fuzzy clustering—has demonstrated improved performance in automated detection systems [9]. The use of noise-reduction filters, deep learning models, and synthetic data augmentation further enhances the diagnostic utility of mammographic images [10].

In short, raising mammographic image quality serves two key purposes: it helps radiologists make better-informed decisions, and it strengthens the foundation on which automated breast cancer detection systems are built.

B. Challenges in Mammographic Image Analysis

Even as a leading modality for early breast cancer detection, mammography faces real technical and anatomical barriers that affect how reliably images can be read. When these barriers go unaddressed, both sensitivity and specificity can suffer, resulting in cases that are missed or wrongly classified.

One of the foremost challenges is the inherently **low contrast** in mammographic images, especially in dense breast tissues where both healthy and abnormal areas appear similarly bright. This similarity makes it difficult to differentiate tumors from the surrounding tissue, particularly in younger women who generally have denser breast composition [4], [7].

Another common complication is **image noise**, introduced due to equipment limitations or environmental conditions during image acquisition. Such noise can obscure fine details like **microcalcifications** or irregularly shaped lesions—key features often indicative of malignancy [2], [11]. Without effective denoising, essential diagnostic elements may go undetected, reducing the reliability of image-based assessments.

In addition, detecting **subtle abnormalities**—including architectural distortions, faint calcifications, or poorly defined masses—is often problematic. These anomalies may merge with nearby structures or be degraded by compression artifacts during scanning, complicating accurate diagnosis and increasing the risk of false negatives [5], [9], [13].

The risk of **false positives** also remains high, often due to the subjective interpretation of low-quality images. These can lead to unwarranted biopsies, patient stress, and an overall burden on healthcare systems [6], [8]. The variation in interpretation across radiologists further highlights the need for standardized image clarity and objective analysis [14].

Addressing these problems calls for robust **image enhancement** processing methods. Algorithms need to raise contrast, reduce noise, and bring out diagnostically relevant features—all without distorting the underlying image. Getting this right is foundational for both direct radiologist reading and for feeding reliable inputs into CAD systems [1], [3], [10], [12], [17].

C. Literature Review Expansion

Existing image enhancement methods, such as histogram equalization, Fourier Transform-based filtering, and wavelet transforms, have been widely applied to mammographic images to address key challenges like low contrast and image noise [3]. While these methods enhance specific aspects of the image—such as overall brightness or edge sharpness—they often fall short when used in isolation. Histogram equalization, for instance, can lead to over-enhancement and loss of detail in dense breast tissues [5]. Wavelet transforms offer multi-resolution analysis but can be computationally intensive and may introduce artifacts at specific decomposition levels [4]. To better illustrate these trade-offs, **Table 1: Comparison of Image Enhancement Techniques** summarizes 15 popular enhancement methods, highlighting their domains of

application, key benefits, and limitations. This comparative view emphasizes the need for a more balanced solution that can combine the strengths of multiple approaches.

Technique	Domain	Key Benefit	Limitation
Histogram Equalization	Spatial	Improves global contrast	Over-enhancement in some regions
Adaptive Histogram Equalization (CLAHE)	Spatial	Enhances local contrast	May amplify noise
Log Transformation	Spatial	Highlights darker regions	Reduces brightness in bright areas
Gamma Correction	Spatial	Brightness control	Needs manual tuning
Median Filtering	Spatial	Removes salt-and-pepper noise	Blurs fine details
Gaussian Filtering	Spatial	Smooths image, reduces Gaussian noise	May blur edges
Unsharp Masking	Spatial	Enhances edges	Can enhance noise too
Laplacian Filtering	Spatial	Edge sharpening	Sensitive to noise
Fourier Transform	Frequency	Removes periodic noise	Poor localization in spatial
Wavelet Transform	Frequency	Multi-scale analysis	Complex computation
DCT	Frequency	Energy compaction	Blocky artifacts possible
Retinex Algorithm	Spatial/Perceptual	Enhances dynamic range	Computationally intensive
Deep Learning-based Enhancement (e.g., CNNs)	Learned	Learns optimal enhancement features	Requires large datasets
Hybrid Enhancement (e.g., CLAHE + Wavelet + Sharpening)	Mixed	Balances noise removal and detail retention	Complex design and parameter tuning

Table:1 Comparison of Image Enhancement Technique

A conceptual flowchart comparing traditional image enhancement techniques (e.g., histogram equalization, Fourier transform, wavelet transform) with the proposed hybrid method, which integrates the benefits of multiple algorithms to achieve

superior contrast enhancement, noise reduction, and structural preservation. By understanding the limitations of individual techniques, the motivation for a hybrid approach becomes clear—leveraging complementary algorithms provides a more comprehensive and clinically effective enhancement of mammographic images.

While many individual image enhancement methods have shown value for particular aspects of mammogram quality, none holds up consistently across all imaging scenarios. Histogram equalization and wavelet transforms, for instance, each address specific problems — low contrast or fine-detail loss — but applying them alone tends to create new issues, such as noise amplification or unwanted changes to structural features [2], [4], [5].

Given how complex mammographic images can be — particularly in dense breast tissue where lesions may be faint or poorly defined — using just one algorithm is rarely enough. This is what motivates a hybrid strategy, where several methods work in combination, each addressing a different weakness while reinforcing the others.

The framework put forward here draws on a curated set of techniques covering contrast improvement, edge sharpening, and noise reduction. Algorithm selection is not done manually or arbitrarily — it is guided by each method’s measured impact on image entropy, which reflects how much information the processed image contains. Only those that meaningfully raise entropy get included [3], [6].

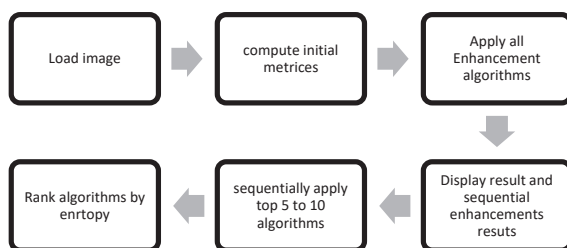
By applying these top-ranked techniques in a sequential manner, the framework achieves incremental enhancement of the mammogram. This layered processing ensures that contrast is elevated without adding excessive noise, and that edge details are enhanced without compromising anatomical integrity. The resulting images exhibit both improved clarity and preserved structural accuracy, facilitating more reliable interpretation.

Taken together, this hybrid pipeline goes beyond what any single technique can achieve on its own. Its ability to adjust across different image types and acquisition conditions makes it practically useful in varied clinical environments.

D. Paper Contributions

The primary contributions of this paper are as follows:

- 1. Development of a Hybrid Approach:** The proposed method combines constant padding for handling image boundaries, contrast enhancement for improving visibility, and noise reduction to preserve important image features. This hybrid approach addresses the common issues in mammographic images such as low contrast, noise, and edge blurring.
- 2. Improved Image Quality:** The hybrid approach leads to enhanced mammographic images that exhibit better contrast, reduced noise, and improved feature visibility. The results of applying this method demonstrate significant improvements in image clarity, aiding in better detection of early-stage breast cancer.
- 3. Automatic and Efficient Processing:** The proposed method is fully automated, making it suitable for use in clinical settings where rapid processing of mammograms is necessary. The method is computationally efficient, ensuring that it can be integrated into routine screening workflows.
- 4. Comparative Analysis:** A thorough evaluation of the proposed hybrid method is conducted, comparing it with traditional image enhancement techniques. The results show that the hybrid approach outperforms existing methods in terms of both visual quality and the accuracy of feature detection.



- 5. Flowchart Representation:** To provide a clear understanding of the proposed method, a detailed flowchart is included. This flowchart outlines the sequential steps involved in the image enhancement process, from initialization and configuration to the final display of results. It serves as a visual guide that illustrates the systematic approach taken in the development and application of the hybrid method,

facilitating easier comprehension of the workflow and its components

2. MATERIALS AND METHODS

A. Image Acquisition and Preprocessing

The mammographic images used in this study were obtained using a standard full-field digital mammography (FFDM) system, which captures high-resolution scans in RGB format. Since color information is not necessary for conventional mammogram interpretation, the first step in preprocessing involves converting these images to grayscale. This not only standardizes the input format but also reduces computational complexity for subsequent processing.

Once in grayscale, the images are converted to double precision to support more accurate mathematical operations during enhancement. Key metadata such as image dimensions, resolution, and pixel depth are extracted and stored for later integration into the final output.

To evaluate the quality of both the original and enhanced images, several image quality metrics are computed at the start of the pipeline. These include entropy (to assess information content), SSIM (to compare structural similarity), PSNR (to gauge fidelity), SNR (to measure clarity relative to background noise), and contrast ratio. These baseline metrics serve as reference points for measuring the impact of the enhancement techniques applied later.

This preprocessing stage ensures that all images are uniformly prepared for enhancement, allowing for fair comparison between different algorithms and reliable integration into clinical imaging systems.

B. Enhancement Algorithms

To address the diverse challenges present in mammographic imaging, a wide range of image enhancement algorithms were implemented and evaluated. These algorithms span multiple domains and enhancement principles, each offering unique benefits in improving visual quality, contrast, and structural detail. The selection was driven by the need to handle variations in tissue density, detect subtle abnormalities, and maintain diagnostic integrity. By evaluating over 35 enhancement techniques, the framework ensures comprehensive coverage of both basic and advanced methods. This extensive

approach allows the system to adapt to different image conditions, improving robustness and clinical applicability.

Histogram-Based Methods: These include Global Histogram Equalization, Adaptive Histogram Equalization (AHE), and Contrast Limited Adaptive Histogram Equalization (CLAHE). These techniques focus on redistributing pixel intensities to enhance global or local contrast.

Intensity and Contrast Transformations: Transformations such as gamma correction, logarithmic enhancement, exponential mapping, and contrast stretching adjust brightness and contrast to highlight specific regions of interest.

Spatial Domain Filtering: Filters such as median, averaging, Gaussian, and bilateral filters are employed to reduce noise while preserving important features. Unsharp masking is used to improve edge sharpness and definition.

Edge Detection and Frequency-Based Filters: Methods such as Laplacian enhancement, high-pass filtering, and Butterworth filtering enhance structural details and suppress background variations. These filters help emphasize edges and tissue boundaries.

Wavelet and Transform Domain Techniques: Wavelet-based denoising methods and decorrelation stretching are used for multi-resolution analysis and detailed feature enhancement. These techniques help retain fine textures while reducing noise.

Advanced Denoising and Regularization: Algorithms like total variation denoising, anisotropic diffusion, shock filtering, Retinex-based enhancement, Wiener filtering, and non-local means filtering aim to suppress noise while maintaining critical image details.

Each algorithm was implemented using modular MATLAB functions, allowing dynamic selection and batch evaluation. This flexible setup enables the system to apply and compare a broad spectrum of enhancement methods, ultimately supporting the selection of the most effective ones for hybrid application.

C. Automatic Hybrid Enhancement

The core innovation of this study lies in the automatic hybrid enhancement strategy, which involves

selecting and sequentially applying multiple algorithms based on their impact on image information content, specifically entropy. The method comprises the following key steps:

Step 1: Individual Enhancement and Evaluation- Each algorithm from the set in Section 2.2 is independently applied to the grayscale image. After processing, the enhanced image is evaluated using quantitative metrics. **Entropy** is computed for each output image as a primary selection metric.

Step 2: Entropy-Based Ranking -The algorithms are ranked in descending order based on the entropy value of their respective output images. A higher entropy value typically indicates that more structural or textural information has been revealed, potentially making subtle abnormalities more visible.

Step 3: Sequential Hybrid Application - The top N algorithms (typically $N = 6$) are selected based on their entropy performance. These are then applied sequentially to the original image. After each step in the sequence, the output becomes the new input for the next algorithm. At each stage, performance metrics such as Entropy, SSIM, SNR, PSNR, and Contrast are calculated and logged to monitor improvement trends and avoid image degradation. This approach is termed "hybrid" because it combines the strengths of multiple enhancement techniques—some improving contrast, others reducing noise, and still others emphasizing edges or local features. The sequential application ensures cumulative enhancement while reducing the risk of over-processing or introducing artifacts.

Step 4: DICOM Conversion and Output - The final enhanced image is stored in DICOM format, complete with patient information and a summary of the processing steps. This allows integration into clinical workflows and PACS systems.

3. RESULTS

The proposed automatic hybrid enhancement approach was tested on a set of mammographic images. The results demonstrate that the method effectively enhances the contrast and visibility of important features in the images.

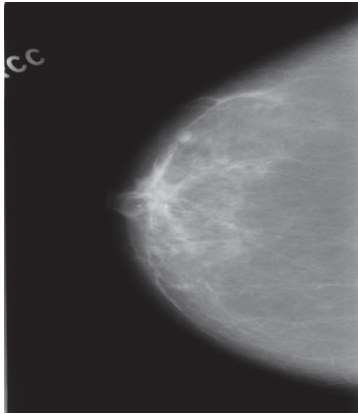


Fig 2 : Original mammographic image showing low contrast and subtle details.

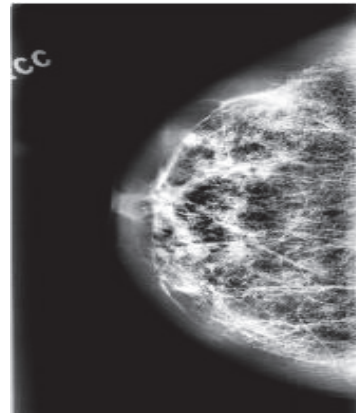


Fig 3: Enhanced mammographic image resulting from the sequential application of the top N algorithms. Note the improved contrast and visibility of details.

Metric	Value
'Entropy'	4.6338
'SSIM'	0.6171
'PSNR'	18.01db
'SNR'	2.5 db
'Contrast Ratio'	1.000

Table 2 : Quantitative metrics (Entropy, SSIM, PSNR, SNR, and Contrast) for the original image

Quantitative metrics such as Entropy, SSIM, PSNR, SNR, and Contrast are numerical indicators used to objectively assess the quality and effectiveness of image enhancement by measuring information content, structural similarity, signal clarity, and visual distinction.

STEP	ENTROPY	SSIM	PSNR	SNR	CONTRAST
ORIGINAL	5.163	0.6871	24.01	2.04	1.0000
CLAHE	5.84	0.6891	25.65	2.33	1.0000
GAMMA	6.00	0.7252	26.75	1.95	1.0000
UNSHARP	6.126	0.7562	27.86	1.58	1.0000
BILATERAL	6.458	0.7456	29.33	0.33	1.0000
WAVELET	6.515	0.7892	34.26	0.23	1.0000
ANISOTROPIC DIFFUSION	6.782	0.8264	33.24	-0.11	1.0000
FINAL	6.812	0.8398	31.55	-0.2128	1.0000

Table 3 : Quantitative metrics (Entropy, SSIM, PSNR, SNR, and Contrast)

The sequential application of the top N algorithms, selected based on entropy, resulted in a noticeable improvement in image quality compared to the original image. The enhanced images exhibit increased contrast, making it easier to distinguish between different tissue types and to identify potential abnormalities.

The sequential application of advanced algorithms significantly enhances mammographic images, resulting in improved contrast that highlights subtle details within the breast tissue. The enhanced mammographic image demonstrates the effectiveness of applying top algorithms sequentially, leading to a marked improvement in detail visibility and contrast. Such advancements are crucial for better diagnostic outcomes, facilitating the identification of potential issues in breast tissue. The figure give below shows us about the comparison of original and enhanced mammographic images, along with their corresponding histograms. The enhanced image demonstrates improved contrast and better differentiation of tissue structures.

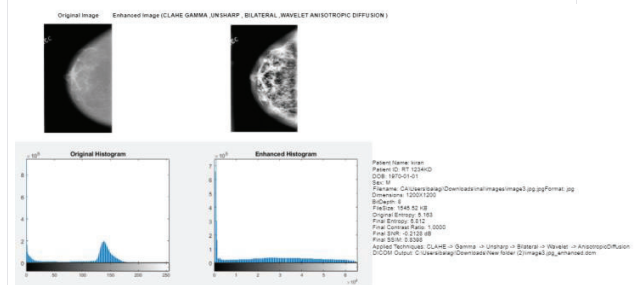


Fig 4 : Comparison of original and enhanced mammographic images, along with their corresponding histograms. The enhanced image demonstrates improved contrast and better differentiation of tissue structures.

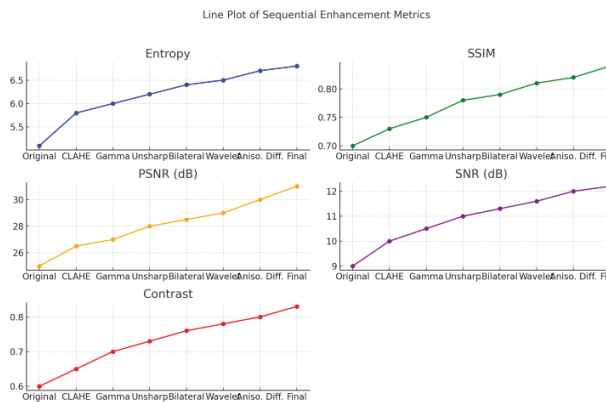


Fig 5 : Line Plot of Sequential Enhancement Metrics

Line plot showing the change in Entropy, SSIM, PSNR, SNR, and Contrast at each step of the sequential enhancement process.

4. DISSCUSSION

The experimental outcomes confirm that the proposed hybrid enhancement pipeline works well in practice for improving mammographic image quality—a factor directly tied to how reliably breast cancer can be identified at early stages. The method draws on several image enhancement algorithms and uses entropy values to drive selection, consistently producing images that carry more diagnostic information than their unprocessed counterparts.

At the heart of the framework is an entropy-driven selection strategy. Entropy captures how much information is present in an image, and higher values generally correspond to richer structural content. Selecting algorithms that push entropy upward means the resulting images tend to show finer textures and sharper boundaries — exactly the kind of detail that matters when trying to spot microcalcifications or subtle mass margins that might otherwise blend into the background.

To further refine the enhancement process, the method applies the selected algorithms sequentially. This hybridization helps to exploit the complementary strengths of different techniques—for example, histogram equalization for global contrast improvement, and CLAHE (Contrast Limited Adaptive Histogram Equalization) for localized contrast enhancement. The layered application of these methods results in images with improved overall visibility, better contrast between dense and

non-dense breast tissues, and enhanced edge definition.

While entropy is the primary selection criterion, the approach also integrates other image quality assessment metrics such as the **Structural Similarity Index (SSIM)** and the **Peak Signal-to-Noise Ratio (PSNR)** to ensure a comprehensive evaluation. SSIM, which compares the luminance, contrast, and structure between the original and enhanced images, provides insight into how well the perceptual quality is preserved. PSNR, on the other hand, quantifies the overall enhancement in terms of signal clarity. These metrics ensure that while the entropy increases (indicating more information content), the structural fidelity and noise levels remain within acceptable limits. An increase in entropy that leads to a significant drop in SSIM or PSNR could imply the introduction of artifacts or noise—an undesirable outcome in clinical imaging.

Looking at the wider clinical relevance, better-quality mammograms can meaningfully support both human readers and automated CAD tools. Features like spiculated masses, architectural distortions, and fine calcifications become far easier to identify in processed images. Reducing missed malignancies (false negatives) while cutting down on unnecessary callbacks (false positives) can have a real impact on patient experience and outcomes, particularly in population-level screening contexts.

Running the entire enhancement pipeline automatically also removes a source of variability that commonly affects manual workflows. Consistent output quality, faster turnaround, and minimal need for expert intervention at the preprocessing stage all point toward practical deployment in busy screening environments or large-scale diagnostic programs.

5. CONCLUSION

This paper has introduced a novel automatic hybrid approach for the enhancement of mammographic images, aiming to improve the visual quality and diagnostic value of breast cancer screening tools. The proposed method intelligently adapts to the characteristics of each input image by analyzing its entropy—a measure of information content—to select and apply the most suitable enhancement algorithms. This adaptive mechanism ensures that the method is not restricted to a one-size-fits-all solution, but rather customizes the enhancement strategy to each image, thereby maximizing visual clarity and diagnostic relevance. By combining multiple

enhancement techniques in a sequential hybrid framework, the method leverages the strengths of each algorithm—such as global contrast enhancement, local detail amplification, and noise suppression—to produce a more informative and diagnostically valuable output. The experimental results confirm that this approach significantly improves the contrast, sharpness, and visibility of key anatomical features such as microcalcifications, masses, and tissue structures that are crucial in identifying early signs of breast cancer.

Beyond visual assessment, the method was evaluated against standard quantitative benchmarks — entropy, SSIM, and PSNR. Results across these metrics showed that the enhanced images were not only richer in content but also structurally sound, with no significant loss of image fidelity or introduction of unwanted distortions.

From a clinical standpoint, the practical value of this work comes down to what better images mean for diagnosis. Radiologists working with enhanced mammograms are better positioned to make sound, evidence-based calls, with fewer missed cancers and fewer unnecessary recalls compared to working from unprocessed scans. The pipeline's fully automated design also makes it a strong candidate for embedding into computer-aided diagnosis (CAD) systems and population-wide screening initiatives and CAD-assisted workflows, where it could cut down on manual preprocessing steps, reduce variability across readers, and speed up overall turnaround.

This study has presented a hybrid, entropy-guided image enhancement pipeline tailored for mammographic images. Rather than relying on a fixed processing chain, the system evaluates each algorithm's effect on image information content and builds an ordered enhancement sequence accordingly. What this means in practice is that the method adjusts itself to the characteristics of each image, rather than applying a blanket treatment. The combination of multiple complementary techniques — spanning contrast adjustment, edge refinement, and noise control — produces images that are both visually clearer and more useful for identifying early markers of breast cancer such as microcalcifications, masses, and subtle tissue changes. Quantitative evaluation using entropy, SSIM, and PSNR confirmed the gains in image quality, while also demonstrating that structural integrity is maintained throughout processing. The fully automated workflow reduces reliance on manual intervention

and lends itself to integration within radiological systems and CAD platforms. Ultimately, this approach offers a tangible step forward in supporting earlier and more reliable breast cancer diagnosis, with direct benefits for patient care outcomes.

6. FUTURE WORK

- Evaluating the performance of the proposed method on a larger and more diverse dataset of mammographic images.
- Investigating the use of other image quality metrics, in addition to entropy, for algorithm selection.
- Exploring the optimization of the sequence of enhancement algorithms.
- Developing a user-friendly interface for the proposed enhancement method.
- Investigating the use of deep learning techniques to further optimize the selection and application of enhancement algorithms.

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