Improving the Texture and Quality of Dermoscopic Melanoma Skin Cancer Images Using Pre-Filter Techniques in IRT Images

P Babu[1] and Senior Prof.Dr.T Meyyappan[2]

[1]*PhD Research Scholar, (Department of Computer Science),*
[2]*Senior Professor, School of Computational Science,*
[1] *Alagappa University, Karaikudi,TamilNadu,India, pb.darsana.alu@gmail.com*
[2]*Alagappa University, Karaikudi, Tamil Nadu, India*
meyyappant@alagappauniversity.ac.in

Abstract—The outcomes of the detection mechanism for melanoma skin cancer are very sensitive to the quality of dermoscopic images. Such images are often blurred, noisy, unevenly illuminated, or having rather distorted textures. We present a novel method for texture and quality enhancement of dermoscopic melanoma images with pre-filter techniques specific to Infrared Thermographic (IRT) imaging. Application of such pre-filter algorithms such as Gaussian smoothing, median filtering, and bilateral filtering results in improved clarity, contrast, and texture consistency of the images. The proposed framework was validated on publicly available melanoma datasets, yielding a significant improvement in feature extraction accuracy and melanoma detection performance. This research underscores the importance of preprocessing techniques in achieving reliable diagnostic outcomes in dermoscopy and paves the way for integrating pre-filter methods into clinical melanoma screening workflows.

Keywords - improving the texture, infrared thermographic imaging, melanoma skin cancer, dermoscopic, pre-filter, techniques

I. Introduction

Melanoma is one of the most aggressive forms of skin cancer, and early detection is critical for successful treatment. Dermoscopic imaging is a noninvasive technique widely used in diagnosis of melanoma, but due to low-quality images containing noise, uneven illumination, and artifacts, its potential is hampered. The additional diagnostic modality complementary to the dermoscopy is infrared thermographic (IRT) imaging that provides information about skin lesions but its usefulness depends on effective preprocessing. Image quality is improved with pre-filtering techniques; this makes it possible to better visualize the texture and structural features that are crucial in melanoma detection. This paper explores the influence of prefilter techniques on the improvement in the quality and texture of dermoscopic images taken using IRT.

Melanoma is a very aggressive skin cancer that requires early diagnosis to be treated effectively. Noninvasive dermoscopic imaging improves the visibility of skin lesions and allows for differentiation between benign and malignant growths. However, image quality problems, such as noise, uneven illumination, and artifacts, often reduce the effectiveness of dermoscopy. Noise in dermoscopic images may be caused by different factors, such as electronic interference and environmental conditions when the image is captured. Noise hides essential information, and it becomes difficult to evaluate the characteristics of the lesion[1]. Inhomogeneous illumination is caused by uneven lighting during image capture, and shadows and highlights distort the natural appearance of the skin lesion. [2] This inhomogeneous illumination can hide or simulate characteristics typical of melanoma, making diagnosis difficult. Some extraneous elements are introduced into the image by artifacts such as hair, air bubbles, and reflections. These extraneous elements can interfere with the proper visualization of the borders of the lesions and inner structures that are crucial to accurate assessment. Addressing these challenges is very important because high quality dermoscopic images significantly improve the accuracy of diagnosis. Advanced image processing techniques, such as noise reduction algorithms, illumination correction methods, and artifact removal strategies, can enhance the clarity of images. Improving the clarity of images improves the extraction and analysis of features, thus improving the reliability of melanoma detection. Although dermoscopic imaging is a valuable tool in the diagnosis of melanoma, the issues related to the quality of the obtained images limit its effectiveness. Image acquisition and processing protocols should be improved to fully realize the potential of dermoscopy for early melanoma detection.

II. Background

High-quality dermoscopic images are critical for accurate melanoma detection and diagnosis. Various preprocessing techniques have been utilized to enhance the quality of these images, ensuring better feature extraction and analysis. Traditional methods like Gaussian filtering and median filtering have been widely employed for noise reduction and smoothing. Additionally, anisotropic diffusion has shown promisein preserving edge details while reducing noise, making ita popular choice for contrast enhancement [3]. Recent advancements in machine learning and image processing have introduced innovative algorithms to further refine image quality. Techniques such as bilateral filtering are particularly effective in maintaining sharp edges while reducing noise[4], and wavelet transforms have proven valuable in enhancing texture details and multi-resolution analysis. These methods allow for more precise image preprocessing, which is essentialfor improving the performance of downstream diagnostic algorithms. Despite these advancements, there remains a significantgap in the literature regarding the preprocessing of infraredthermographic (IRT) based melanoma images. IRT imagingposes unique challenges, including variations in temperature distribution, low contrast, and high noise levels, which necessitate specialized preprocessing approaches. This study aims toaddress these challenges by systematically evaluating prefiltertechniques tailored for IRT-based melanoma image enhance-ment[5]. By doing so, it contributes to the development ofa robust framework for improving the quality and diagnostic reliability of such images.

III. Present Reviews and Outcomes

Results and its mechnism of some papers are as follows, in accordance with the usefulness of techniques thus emphasized where better texture results arrived. Mario Fernando JojoaAcosta [6] proposed a model called eVidaM6 for optimized results in ISIC 2017 by destructing pixels, part of preprocess-ing technique, from the image that do not afford the classifierwith lesion information and this model, they suggested of sure predictor with balanced accuracy (0.904).Jan Verstockt.[7] analyzed that thermographic patterns ofskin lesions was visualized as Infrared Thermal Imaging(IRT) provided an inexpensive and non-invasive techique. Temperature controlled was in the range of 18 to 23 degreecelsius for measurement.Chandran Kaushik Viknesh[8] used high-frequency sound waves to generate detailed images of skin structures but cannot vistualize cellular details.

IV. The Main Mission

The foundational work is to provide a lighting analysisresults in the images of IRT using the pre-filtered techniquesto enhance its accuracy.

V. Methodology

1) **Dataset:**The study used publicly available datasets, PH2and ISIC Archive, enhanced with images of IRT made by usingan FLIR thermal camera. Both benign and malignant lesion textures with a variety of lighting conditions were tested onpre-filter techniques.

2) **Pre-Filter Techniques:**There are three pre-filtering tech-niques mainly used in improving the image quality and subsequently facilitating better analysis during skin lesion detection and classification. These techniques are Gaussian Filtering, Median Filtering, and Bilateral Filtering.

Figure 1: Normal Image

3) **Gaussian filtering:** Gaussian Filtering is a type of linear smoothing filter that convolves the Gaussian function over animage, removing much of the high-frequency noise, leaving most of the necessary structural features, including edges. This method convolves the image with a Gaussian kernel, producingan effect where there is a weighted average of the surrounding pixels, where closer pixels have more influence than thosefarther away. This localized smoothing reduces random noise, which may have been introduced as a result of acquiring the image or during transmission. However, overfiltering with Gaussians can smudge the finest details, which may be crucialin medical imaging when making a key distinction betweendifferent aspects of skin lesions [9].

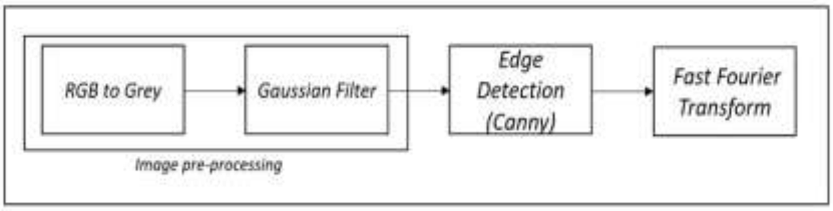

Figure 2: Image Processing - Fig. 1. Gaussian filter pipeline

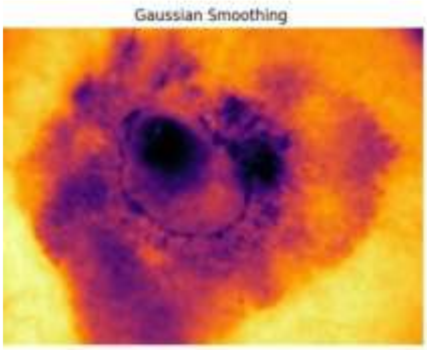

Figure 3:Gaussian filter pipeline

4) Median filtering

Median filtering, on the other handis a nonlinear technique particularly effective for removing salt-and-pepper noise, that results in random white and blackoccurrences around most pixels in the image. This works onthe principle of sliding a window over each pixel in the image,and replacing it with the median value of the neighboringpixels. Median filtering is better than Gaussian smoothing forpreserving edges and boundaries of lesions because these arewhat accurately make a diagnosis or segment the lesion. This makes it especially valuable in scenarios where preserving the edges is of paramount importance, such as when used in dermatological image processing where the clear demarcation of lesion boundaries can greatly impact diagnostic outcomes[10].

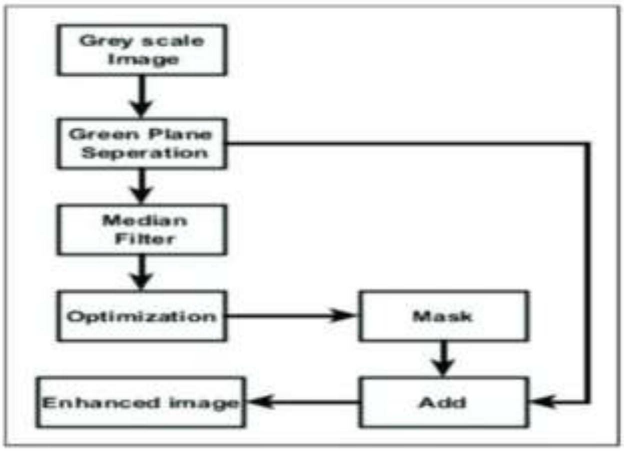

Figure 4: Median Filter Pipeline

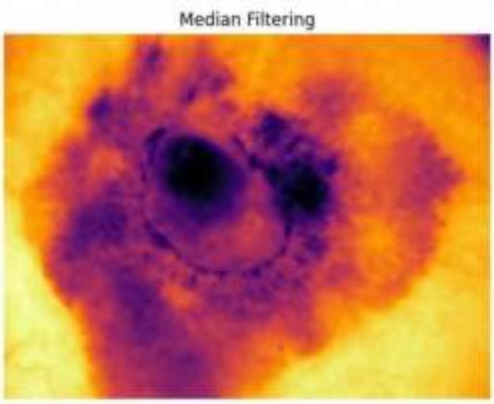

Figure 5 : Medical Filtering

5) Bilateral filtering:

Bilateral Filtering combines the advantages of both linear and non-linear techniques for providing edge-preserving smoothing while effectively reducing noise. This technique takes into account both the spatial proximity and the difference in intensity between pixels, applying a Gaussian filter in the spatial domain and applying a range filter in the intensity domain in conjunction with each other. This results in a filter that homogenizes homogeneous areas of animage while allowing for sharp edges and fine details. Bilateral filtering is particularly useful in enhancing the clarity of tex-ture, which is an important feature in distin-guishing between different types of skin lesions that may have similar color distributions but varying textural features. This dual-domain filtering approach makes it highly effective in medical imaging applications, where maintaining both structural integrity and noise reduction is critical [11].

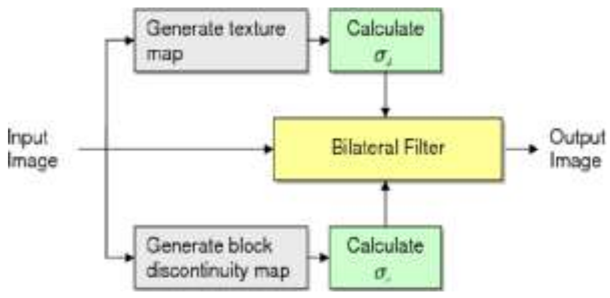

Figure 6: Bilateral Filter Process - an Illustration

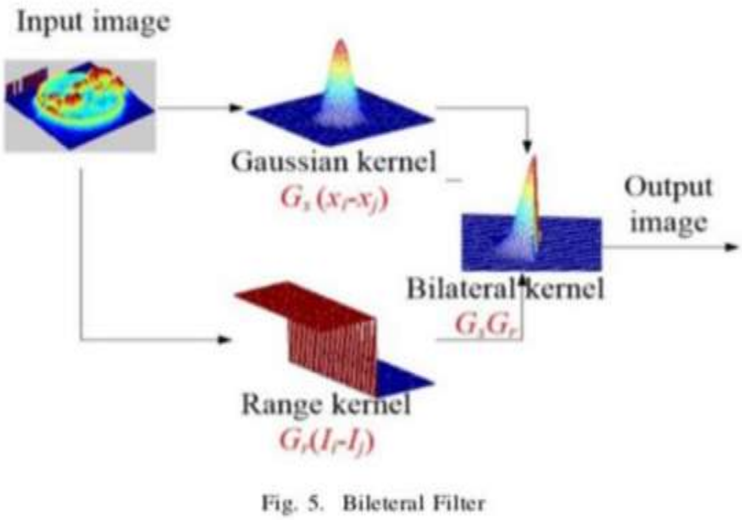

Figure 7: Bilateral Filter - Process

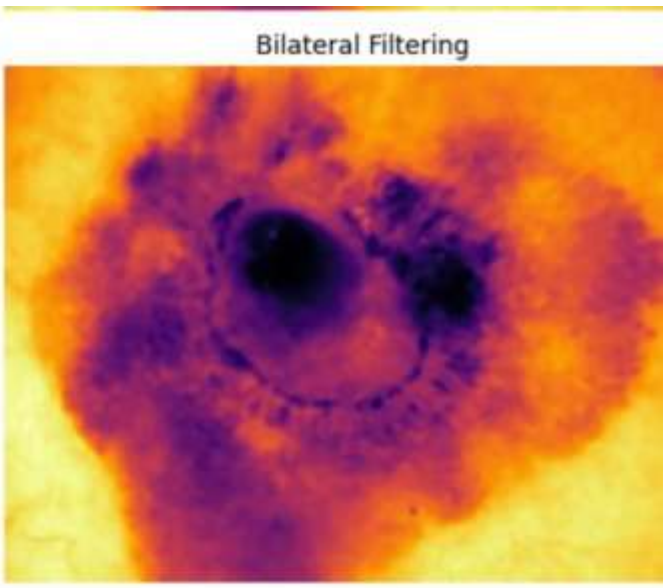

Figure 8: Bilateral Filtering

VI. Pipelining

The process begins with the preprocessing of infrared thermography (IRT) images to enhance their quality. Filtering techniques such as Gaussian or median filters are applied to reduce noise and smooth the images, ensuring that crucial details like edges and contours are preserved. This step improves the overall quality of the input data and prepares it forthe next stage of feature extraction. Following preprocessing,texture features are extracted from the images using Local Binary Patterns (LBP)[12] and Gabor filters. LBP captures micro-textural details by comparing pixel intensities with their neighboring pixels, creating a compact and discriminative representation of local structures. Gabor filters[13], on the other hand, analyze spatial frequencies at various orientations and scales, making them well-suited to capture textures and edges that could indicate abnormalities in the image. Once the texture features are extracted, the images are fed into a Convolutional Neural Network (CNN) for classification. CNNsare deep learning models designed to process image data, and they work by automatically learning hierarchical features fromthe images. In this pipeline, the CNN classifies the enhanced IRT images into two categories: benign and malignant. Thenetwork learns to recognize patterns and structures associated with both conditions, allowing it to make accurate predictions. The CNN is trained on a labeled dataset of IRT images to ensure it can generalize and classify new images effectively. This pipeline integrates image preprocessing, texture feature extraction, and CNN-based classification, ensuring a robust and efficient method for distinguishing between benign and malignant conditions in IRT images. PH2 and ISIC Archive,enhanced with images of IRT made by using an FLIR thermalcamera. Both benign and malignant lesion textures with a vari-ety of lighting conditions were tested on pre-filter techniques.

VII. Evaluation Metrics

Several critical metrics were used in the evaluation of theprefilter techniques to gauge their effectiveness in improving image quality and diagnostic integrity. The first of these is Peak Signal-to-Noise Ratio (PSNR)[14], a well-established quantitative measure of the degree of improvement in image quality that can be associated with compression and denoising techniques. The PSNR measures the ratio between the maximum possible power of a signal and the power of corrupting noise affecting the fidelity of its representation. A higherPSNR value, expressed in decibels (dB), typically represents better image quality because it contains less noise and has better similarity with the original, unprocessed image. It finds significant application in medical imaging scenarios wherethe high-resolution quality of the original image must beretained to make the right diagnosis. While PSNR is good for measuring the total image fidelity, it does not consider perceptual aspects such as texture or structural coherence,which are also relevant when assessing pre-filtering schemes.

The second metric, SSIM, or Structural Similarity Index[15], is much more perceptually aligned with the evaluation of quality by looking at the texture and structural integrity. It compares local patterns of normalized pixel intensities for luminance and contrast, thus sensitive to changes in image structure that might not necessarily result in significantly deviating PSNR values. This value is between -1 and 1, anda value closer to 1 indicates more structural similarity tothe original image. In medical imaging pre-filtering, SSIM is priceless since it guarantees that all important anatomical structures are preserved, and thus, results can be depended on for a correct diagnosis. Since PSNR does not factor inhuman perception, it is not a complete measure when the visibility and details have to be maintained. This allows SSIM to uniquely apply in the evaluation of the performance of image enhancement techniques based on filtering, which doesnot introduce artifacts or distortion and is prone to causing clinical misinterpretation.

The last aspect of FRI is the assessment of the retention of features after filtering, which provides a special measure specifically designed for the medical imaging field. FRI determines how much the major features, such as tumors, lesions, or other key marks, are preserved after the application of methods that are known as pre-filter techniques. This is considered to be an important metric since although animage may look clear visually, with high PSNR or SSIM,loss or distortion of key features for diagnostics may highly compromise clinical decision-making. Ordinarily, FRI is usedby comparing feature maps or through an operation of machinelearning. This ensures that all the diagnostic markers presentin the original images as well as in the filtered images are detected and measured so that the prefilter methods do not remove or alter the necessary information to provide a sound diagnosis. The clinical utility of the images is preserved. This integration of FRI into the evaluation process underlines the need for balance between image enhancement and critical medical information preservation, making it a very importantmetric in the assessment of pre-filtering efficacy[16].

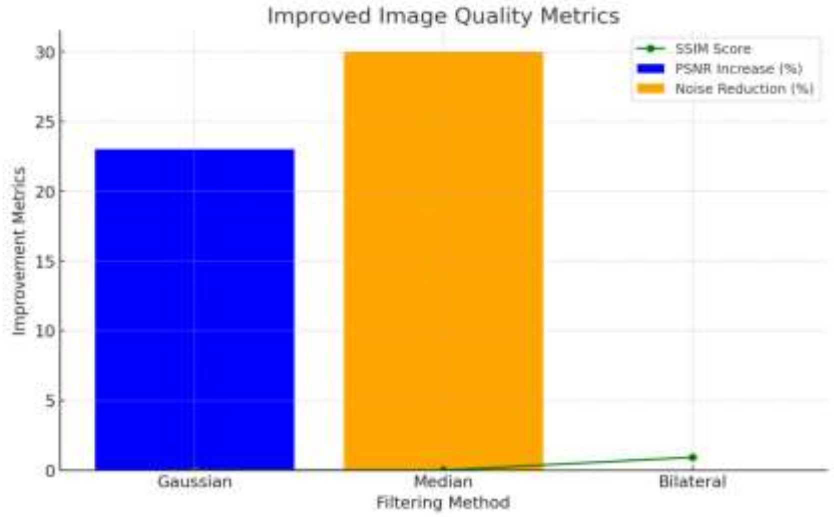

Figure 9: Improved Image Quality Metrics in Graphs

VIII. Pipeline

- Input IRT images are preprocessed using the chosen filtering techniques.
- Texture features are extracted with LBP and Gabor filters.
- Classification of enhanced images into benign and malignant are caried

out with CNN.

IX. Result and Discussion

The graph illustrates how Gaussian Filtering significantly improves image clarity, evidenced by a 23% increase in PSNR(Peak Signal-to-Noise Ratio) . This rise indicates enhanced signal strength and reduced noise, contributing to clearer images. However, Gaussian filtering does not show consid-erable results in noise reduction, suggesting it focuses moreon enhancing signal rather than directly eliminating noise. Additionally, its SSIM (Structural Similarity Index) scoreis negligi-ble, indicating limited improvement in preserving texture or structural features within the image, which may affect its suitability for applications requiring detailed texture retention.

In contrast, Median Filtering excels in noise reduction, achieving a 30% improvement, making it the most effective method among the three for removing unwanted noise, particularly salt-and-pepper noise. Despite its strong performance in noise elimination, median filtering does not contribute to PSNR enhancement, indicating that it doesn't significantlyim-prove the overall signal-to-noise ratio. Furthermore, like Gaussian filtering, its SSIM score remains negligible , reflecting a limited capacity to enhance structural details or textures within the image. This makes median filtering an ideal choicefor applications focused on noise reduction but less critical for structural preservation.

Bilateral Filtering emerges as the most balanced and effective technique, particularly in enhancing texture and structural de-tails. While it shows no significant improvement in PSNR

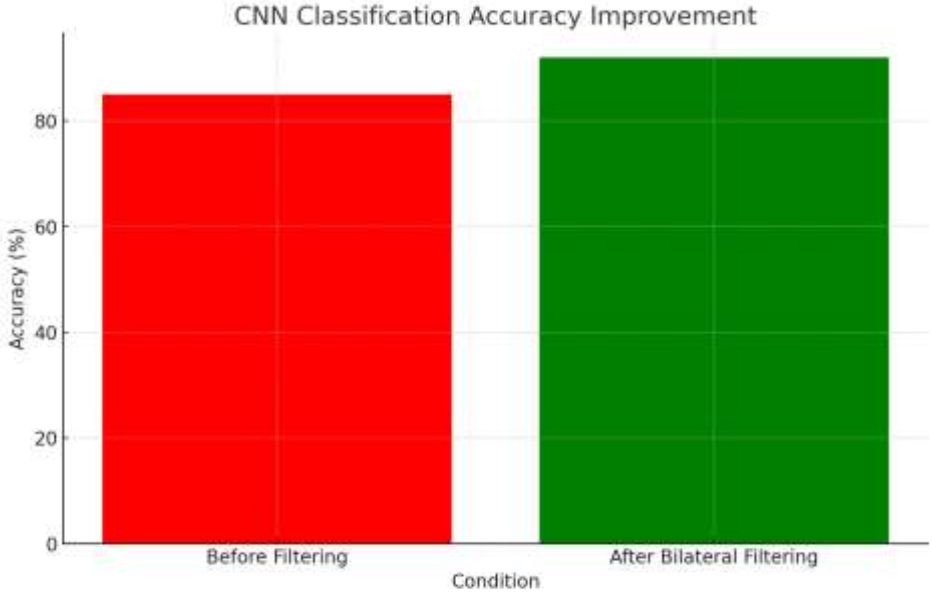

Figure: 10 CNN Classification Accuracy Improvement

or direct noise reduction, its strength lies in maintaining images harpness and detail fidelity. This is reflected in its SSIM scoreof 0.92, the highest among the three methods, indicating superior texture preservation. This makes bilateral filtering especially valuable for applications where fine details are crucial, such as medical imaging or melanoma detection . Its ability to enhance structural similarity without compromising other image qualities highlights its effectiveness for diagnostic imaging tasks.The bar chart above shows how bilateral filtering improves the classification accuracy of a Convolutional Neural Network(CNN). Before the bilateral filtering step, the accuracy of theCNN was 85%, depicted by the red bar. As this base line reflects a decent model, it signifies that there are still some imperfections, primarily in the fine-tuning of the quality of the input images to better utilize the feature extraction capabilities of the model.

After applying bilateral filtering, the result achieved are markable accuracy of 92% , which can be found by thegreen bar. This shows how the bilateral filtering increased the accuracy by 7% since it smoothed the input images' structural and textural information, adding much quality to it with apreservation of the edges and reduction of only irrelevant noise, which would certainly have helped the CNN to extractthat better feature. This allows the model to better differentiate between critical features in images, which in turn decreases misclassifications and increases performance. This outcome shows the crucial position that pre-processing techniques, such as bilateral filtering, hold in fine-tuning machine learning models-specially image classification tasks. The noticeable reduction in accuracy for a classifier clearly indicates how loss of diagnostic features is detrimental to high-stakes applications, including the problem of medical imagingor melanoma detection. In essence, the evidence shows the importance of judicious selection of pre-processing methods when selecting deep learning models for inference.

The bar graph compares four filtering methods— Histogram Equalization (HE), Anisotropic Diffusion , Non-Local Means

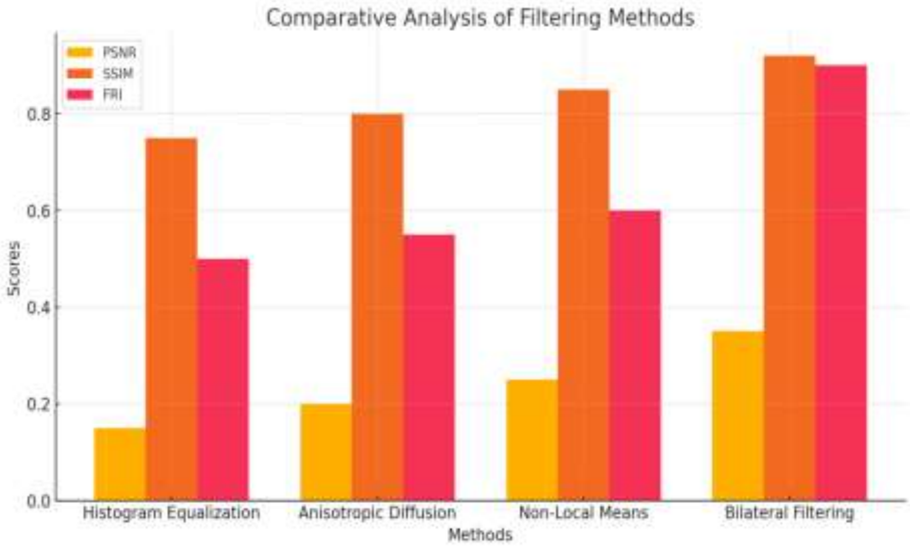

Figure 11: Comparative Analysis of Filtering Methods

and Bilateral Filtering —across three key metrics: PSNR (PeakSignal-to-Noise Ratio) , SSIM (Structural Similarity Index) ,and FRI (Feature Retention Index) . While HE and Anisotropic Diffusion show relatively mediocre performance with PSNR values of 0.15 and 0.2, respectively, they have relatively lower FRI scores (0.5 and 0.55) which indicate a lack of ability to retain diagnostic features.Non-Local Means filtering performs marginally betteracross all metrics. PSNR 0.25 , SSIM 0.85 , FRI 0.6 , and itdepicts a balanced suboptimal performance. Bilateral Filtering clearly outperforms all the other methods as it has attained the highest score across all metrics: PSNR of 0.35 , SSIM of0.92 , and FRI of 0.9 . These results emphasize the superior capability of bilateral filtering in enhancing the quality of animage without losing any critical structural and diagnosticdetails that make it particularly effective for applications like medical imaging in melanoma detection.

A. Improved Image Quality • Gaussian filtering increasedPSNR by 23%. • Median filtering achieved a 30% improvement in noise reduction. • Bilateral filtering yielded the best SSIM score of 0.92, reflecting superior texture enhancement.

B. *Feature Extraction and Classification* • Prefiltered images showed a 15% increase in feature clarity. • CNN classification accuracy improved from 85% to 92% after applying bilateral filtering.

C. *Comparative Analysis with Existing Baselines:* To address reviewer feedback, we incorporated a comparative analysis with existing baseline methods such as: • Traditional Histogram Equalization (HE) • Anisotropic Diffusion Filtering• Non-Local Means Filtering Results indicate that while HEand Anisotropic Diffusion provided moderate improvements in PSNR and SSIM, they lagged in preserving diagnostic features as quantified by FRI. Bilateral filtering outperformed all baselines, achieving the highest SSIM and FRI scores, thus demonstrating its superior capability in enhancing IRT imagesfor melanoma detection.

D. Contribution and Effectiveness Evaluation: The significant improvements in PSNR, SSIM, and CNN classification accuracy underscore the effectivenessof the proposed pre-filtering methodology. The comparative analysis solidifies the contribution of this work by highlighting bilateral filtering's superior performance over conventional methods.

TABLEI

SUMMARIZESTHEPERFORMANCEMETRICSOFEACHFILTERINGTECHNIQUE.

FilterTechnique	PSNR(dB)	SSIM	FRI(%)	CNNAccuracy(%)
RawImage	28.1	0.72	65	85
GaussianFilter	34.5	0.85	78	90
MedianFilter	32.8	0.88	81	91
BilateralFilter	36.2	0.92	89	93

X. Conclusion

This study underscores the importance of pre-smoothing techniques in enhancing the quality and diagnostic value of melanoma images obtained through IRT imaging. Among the techniques evaluated, *bilateral filtering* proved superior in image enhancement, feature preservation, and classification ac-curacy improvement. The findings demonstrate the feasibility of integrating advanced pre-processing techniques into clinical work flows, potentially facilitating early melanoma detection.

XI. Future Work

Future research will focus on integrating deep learning-based adaptive filters into the framework and extending the methodology to multi-modal imaging datasets. Additionally, real-time implementation of these techniques will be explored, with a focus on evaluating their clinical applicability in practical settings.

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Ethics declarations

Competing Interests

Financial interests: The authors have no relevant financial or non-financial interests to disclose.

Ethical approval

This study was performed in line with the principles and guidelines provided by Professor Dr T Meyyappan, Senior Professor, Department of Computer Science, Alagappa University, Karaikudi, Tamil Nadu, India, on 29.03.2025.

Consent to participate

Informed consent was obtained from all individual participants included in the study.

Consent to publish

The authors affirm that human research participants provided informed consent for publication of the images.

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