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Efficient Skin Cancer Image Enhancement Using Log Ratio Difference

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***Abstract*-Skin cancer images are utilized for prediction of cancerous images. The accurate and early detection of skin cancer is crucial for effective treatment and improved patient outcomes. For improving quality, the efficient image enhancement is extremely required. In this paper, an enhancement framework is proposed for skin cancer image enhancement using MedNode dataset. The proposed approach comprises a multi-stage preprocessing techniques, which includes median filtering, Contrast Limited Adaptive Histogram Equalization (CLAHE), Intensity Adjustment and Log Ratio difference methods. The evaluation of proposed methodology is performed using entropy, Peak Signal to Noise Ratio (PSNR), Feature Similarity Index Metrics (FSIM), Spectral similarity Index Metrics (SRSIM), Mean Absolute Error (MAE), and Universal Quality Index (UQI). The proposed methodology outperforms state of the art methods.**

Keywords: Skin cancer, Enhancement, Log ratio difference, CLAHE

1. Introduction

Skin cancer is one of the most prevalent forms of cancer worldwide, with over 5 million cases diagnosed each year in the United States alone [1]. Early and accurate detection is crucial for effective treatment and improved patient outcomes. However, the visual inspection and diagnosis of skin lesions can be challenging, even for experienced dermatologists, due to the subtle variations in the appearance of malignant and benign lesions.

Recent advances in computer vision and machine learning techniques have opened up new avenues for automated skin cancer analysis and classification. One critical component of these systems is the preprocessing and enhancement of skin lesion images. Effective image enhancement algorithms can improve the visibility of diagnostic features, remove artifacts and noise, and normalize the image properties, ultimately leading to improved classification accuracy.

Image enhancement techniques for skin lesion analysis have been an active area of research in recent years. Various methods have been proposed, including contrast enhancement [2], [3], [4]. However, many of these techniques are tailored to specific imaging modalities or cancer types and may not generalize well to diverse clinical scenarios.

This paper proposes a hybrid image enhancement framework for skin cancer image analysis that combines RGB color model conversion to LAB color model, intensity adjustments and log ratio difference techniques. The proposed approach aims to address the limitations of existing methods by improving PSNR, FSIM, SRSIM, MAE and UQI. Extensive experiments

on MedNode dataset demonstrate the effectiveness of our method in enhancing skin cancer images.

2. Literature Review

Enhancement is a crucial preprocessing step in analysis of skin cancer from images. Proper enhancement can improve the visibility of subtle features and details in skin cancer images, which can be further used for essential diagnosis and classification. However, traditional contrast enhancement methods, such as histogram equalization and adaptive histogram equalization, often introduce artifacts, noise, and over-enhancement issues, especially in regions with high contrast or sharp edges. This literature review provides an overview of recent developments in machine learning-based enhancement techniques for skin cancer imaging.

Histogram equalization (HE) is one of the most widely used enhancement techniques [5]. It redistributes the pixel intensities to achieve a more uniform histogram, thereby increasing the contrast of the image. However, HE can introduce undesirable artifacts, such as over-enhancement in relatively homogeneous regions and loss of detail in highly contrasted areas. Adaptive histogram equalization (AHE) is an extension of HE that operates on small image regions (tiles) rather than the entire image [6]. While AHE can enhance local contrast effectively, it often introduces artificial boundaries between tiles, leading to a "tiled" appearance and potential loss of diagnostic information. Other traditional methods, such as gamma correction and contrast limited adaptive histogram equalization (CLAHE), have also been explored for skin lesion image enhancement [7], [8], [9]. However, these methods often require careful parameter tuning and may still struggle with complex contrast variations or noise present in the images.

Mete and Sirakov (2014) used optimal feature selection to diagnose skin cancer with accuracy. The author used a Support Vector Machine with recursive feature removal, which produced results with higher accuracy than previous methods used [10]. According to Giotis et al. (2015), computer vision methods have been at the forefront of automated dermoscopic image processing for the purpose of diagnosing and screening for melanoma. Previous research focused on manually created characteristics input into traditional classifiers like SVMs, such as color, texture, form, and topological descriptors [11]. Because CNNs automatically create hierarchical features, they are among the most widely used deep learning models. A CNN-SVM pipeline with 89.3% sensitivity for classifying melanoma was shown by Codella et al. (2015). Several CNNs together may overcome a significant variance. In order to use texture and color data across dermoscopic channels and achieve a 95% AUC, Menegola et al. (2016) presented an ensemble of 18 CNNs [12]. In order to identify skin lesions, Esteva et al. (2017) offered a Convolutional Neural Network (CNN) model that was trained on more than 100,000 photos. They attained an accuracy of 72.1% that was on par with dermatologists. Utilizing transfer learning from big datasets of natural images was a crucial component. But actual performance was inadequate. [13]. A novel technique to image classification was presented by Matsunaga et al. (2017), which used features obtained from deep CNN activation outputs instead of traditional image pixels or transform coefficients. Melanoma detection using an SVM on these activation vectors was 85.5% accurate [14]. In order to highlight discriminative areas inside lesions, Wang et al. (2019) built a recurrent CNN model that included spatial and channel attention branches. Adoption Requires Explainable DL [15]. A clear deep learning method for the categorization of skin cancer lesions was given by Rehman et al. in 2022. Additional convolution layers are added to the pre-trained MobileNetV2 and DenseNet201 deep learning models in order to properly identify skin cancer. Results indicate that the given Modified DenseNet201 model

achieves 95.50% accuracy and state-of-the-art performance when compared with other approaches reported in the literature [16]. A multimodal fusion method-based technique for classifying skin cancer was proposed by Chen et al. in 2023. In this case, MDFNet successfully creates a mapping between features of heterogeneous data, successfully combines clinical skin pictures with patient clinical data, and successfully addresses the issues of feature scarcity and inadequate feature richness that arise from using just single-mode data. According to the experimental findings, the suggested smart skin cancer detection model has an accuracy of 80.42%, which is around 9% better than the model's performance when using simply medical images [17].

Despite the promising results of machine learning-based image enhancement techniques, several disadvantages are also present. Developing algorithms that can generalize to diverse imaging conditions and lesion types remains a challenge. Developing more transparent and interpretable models could improve trust and adoption in clinical settings. While individual image enhancement techniques have been extensively studied, their impact on the overall performance for skin cancer detection is not always clear. More research is needed to understand the interplay between image enhancement and subsequent classification tasks. In the proposed an efficient methodology is proposed for enhancement of skin cancer images using MedNode dataset.

3. Proposed Methodology

In the proposed methodology, Melanoma skin cancer images from MedNode dataset is taken, and experimentation work is carried out using Matlab 2021a software. The MedNode dataset is one of the large publicly available dataset of skin cancer images collected by the MedNode research group. The images were acquired from different populations across multiple countries, providing diversity in skin tones, lesion types, and imaging conditions. The dataset includes expert annotations for various diagnostic categories such as melanoma, nevus, basal cell carcinoma, and seborrheic keratosis. Each case is accompanied by metadata, including age, sex, anatomical site, and other clinical details. The figure1 describes the steps involved in the enhancement of skin cancer images. The various steps involved are explained as below.

3.1 RGB image splitting

The first step involves taking a color skin cancer image and resizing it to 512 x 512 pixels. It is split into red, green, and blue components. When compared to operations on combined images, the outcomes from operations on each component will be much superior.

3.2 Median filtering

The 3×3 size median filter is used to eliminate the noise that exists in each component. Unwanted features in each component will have an impact on how well images are enhanced. The first thing to do is to get rid of the noise.

3.3 RGB color model LAB color model conversion

The updated RGB version of the skin cancer image is created by merging the red, green, and blue components that were acquired following median filtering. Then, a LAB color space model is created from the revised RGB image. The model of color space in LAB have goal to simulate human perception and vision. About equal perceived color variances by the human eye correspond to equivalent distances in the LAB color space.

3.1.4 CLAHE on ‘L’ component of LAB color model

The LAB color model's "L" component stands for the lightness component. The L component may be used to represent grayscale images or to transform color images to grayscale while maintaining the perceptual brightness information since it indicates lightness. On the "L" portion of the LAB color model, the CLAHE is applied. It can successfully raise the luminance

channel's local contrast when applied to the L component of the LAB color model without causing any undesirable color distortions or artifacts. This ensures that the skin cancer image's original color features are maintained while the luminance channel's contrast is enhanced.

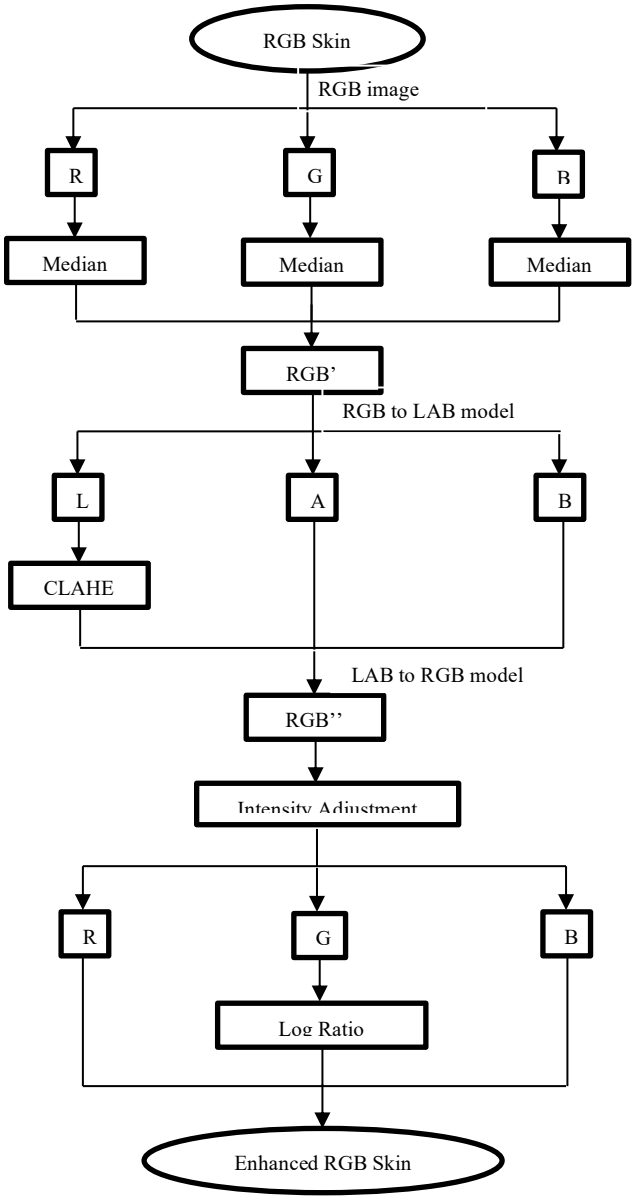


Fig. 1. Proposed methodology for skin cancer images enhancement

3.1.5 LAB color model RGB color model conversion

To create the revised LAB color model of the skin cancer image, the updated "L" and "AB" components are combined. RGB color model is created by converting LAB color model. The updated RGB color model for the skin cancer image is more light-colored than the original.

3.1.6 Intensity Adjustment

Next, the revised RGB image is applied while adjusting its intensity. Adjusting the intensity of the RGB color model is a simple and obvious operation. It entails scaling the values of each of the three color components by a fixed amount that adjusts the image's overall brightness.

3.1.7 Log Ratio Difference on Green channel

The modified RGB image's green channel is subjected to the log ratio difference technique. Subtle changes in the green channel that can be hard to see in the original RGB image might be amplified by the log ratio difference. This may be helpful in identifying and examining small-scale patterns or traits associated with the properties of the image.

3.1.8 Enhanced skin cancer image

The final RGB image is generated by combining the green channel image that was acquired after the log ratio difference was implemented. The final image provide enough features to enable the kind of skin cancer to be detected.

4. Results and Discussions

The MedNode dataset is utilized in the suggested approach for skin cancer image enhancement. The goal of the MedNode dataset is to support the creation and assessment of computer-aided diagnostic systems for skin lesions by compiling a selection of high-quality photos of skin cancer. A dermatoscope is a device that magnifies and lights the skin surface; several high-quality dermoscopic images, or specialized images, are included in this collection. The MedNode collection comprises photos that have been painstakingly annotated and classified based on various skin lesions, including benign nevi (moles), melanoma, and basal cell carcinoma. Since skilled dermatologists usually

give these annotations, precise labeling and ground truth data are guaranteed for machine learning model testing and training. After the application of proposed methodology, some of the resultant enhanced images obtained are represented in figure 2. For Comparative analysis, the commonly used methods applied by researchers [9] were also shown.

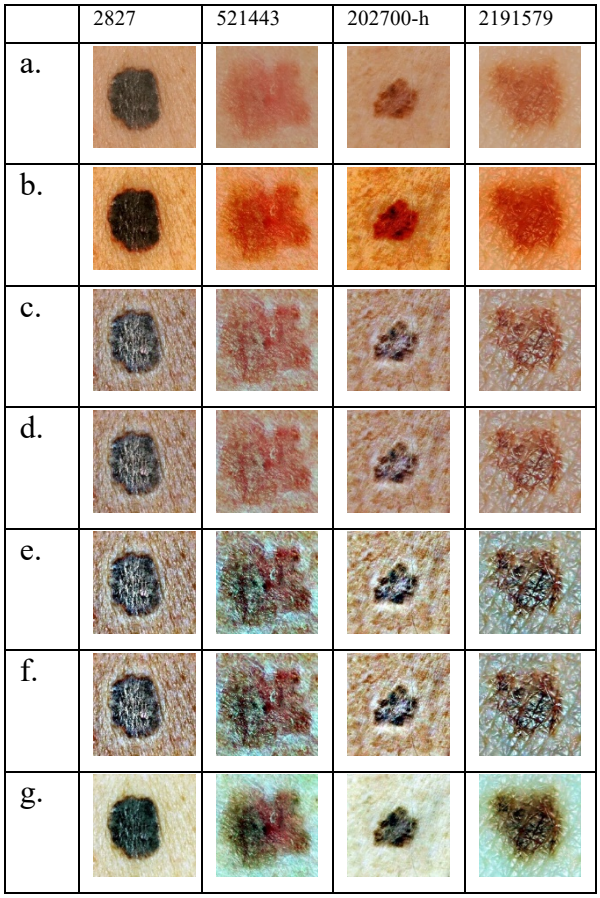


Fig. 2 (a) Original skin cancer image (b) Histogram equalization output image (c) CLAHE output image (d) CLAHE with Gaussian filter (e) CLAHE with Median filter (f) CLAHE with Weiner filter (g) enhanced image using proposed methodology

Evaluation parameters are used in the research work to assess the effectiveness of the proposed methodology for skin cancer image enhancement and analysis. The parameters that are assessed include Entropy, Peak Signal to Noise Ratio (PSNR), Feature Similarity Index Matrix (FSIM), Spectral Similarity Index Matrix (SRSIM), Mean Absolute Error (MAE), and Universal Quality Index (UQI).

The various performance parameters have its independent significance in representing the enhancement technique proposed.

4.1 Entropy

The measure of unpredictability or uncertainty in a data source is called entropy. Entropy may be used to measure the amount of information or randomness in skin cancer images. It is a helpful tool for examining the patterns and texture of the skin image. Higher entropy levels are often indicative of more unpredictability or complexity in the texture of the image, which may be related to certain traits of skin cancer [18].

4.2 Peak Signal to Noise Ratio (PSNR)

Peak signal-to-noise ratio, or PSNR, is a metric used to assess the quality of the image by comparing its greatest signal value to any distortion or noise. PSNR is helpful in evaluating the quality of skin cancer images, which is crucial for precise analysis and diagnosis. Usually, PSNR is determined by contrasting an improved version of the same image with the original. The higher the PSNR value, the better the quality of the enhanced image compared to the original [9].

4.3 Feature Similarity Index Matrix (FSIM)

A metric called the Feature Similarity Index Matrix (FSIM) is used to compare two images according to their low-level characteristics, such texturing, brightness, and gradients. FSIM may be helpful in evaluating the quality of improved images related to skin cancer. Greater values suggest a higher degree of low-level feature similarity between the images. The value of FSIM ranges from 0 to 1 [19].

4.4 Spectral Similarity Index Matrix (SRSIM)

A popular metric for determining how similar two images are to one another perceptually is the Spectral Similarity Index Matrix (SRSIM). It is more suited for assessing picture quality since it considers both luminance distortions and structural information. By contrasting the improved images with the original images, SRSIM may be used to assess how well enhancement methods function in the context of skin

cancer imaging. Higher values imply more structural similarity between the examined images. The SRSIM value ranges from -1 to 1 [20].

4.5 Mean Absolute Error (MAE)

When evaluating enhancement strategies in the context of skin cancer imaging, the Mean Absolute Error (MAE) is a useful measure. The average magnitude of the absolute disparities between the image's ground truth and prediction is measured. To provide an evaluation of the algorithm's performance, MAE is often combined with additional assessment criteria. In general, an enhanced skin cancer image that has a larger mean absolute error (MAE) value than the original image means that the enhancement technique included artifacts or distortions that differ from the original image [21].

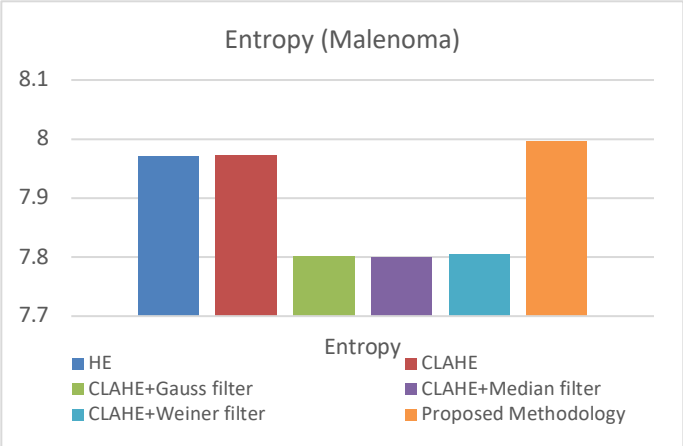
4.6 Universal Quality Index (UQI)

The Universal Quality Index (UQI) is a metric used to assess the quality of images related to skin cancer by taking into account a number of variables, including lighting, contrast, sharpness, and the existence of noise or abnormalities. A high UQI score in the context of skin cancer imaging means that the picture has the best features possible for accurately assessing lesions, such as well-defined borders, suitable contrast between the lesion and surrounding skin, and few distortions or blockages. On the other hand, a low UQI score indicates that the image quality could be weakened, which might make accurate diagnosis or analysis more difficult. The UQI is an important tool for automated quality control and picture selection procedures as it can be calculated using algorithms that take into account expert annotations and domain-specific knowledge [22].

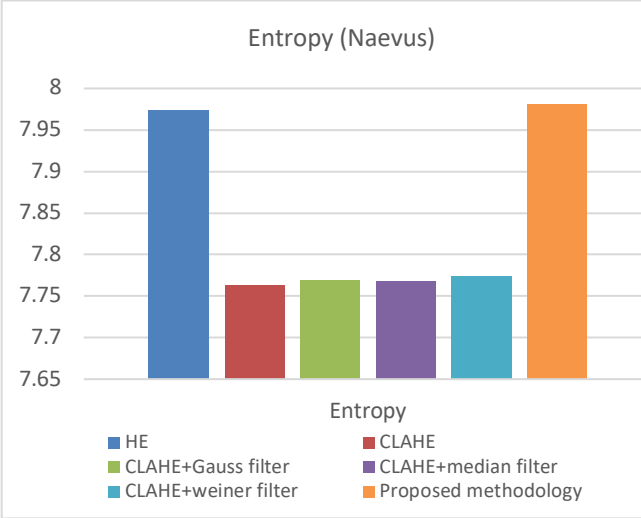
It has been observed that all parameters performed well as compared to other enhancement techniques. The graphical representation of the enhancement results for various methods are performed in figure 3. It has been observed from the graphs that Entropy, PSNR, FSIM, SRSIM and UQI have maximum values for proposed methodology and the error MAE is found to have minimum value for proposed methodology. All of these indicates the proposed method is providing efficient enhancement as compared to other enhancement methods.

Table 1 Comparison of different enhancement methods with respect to the proposed methodology

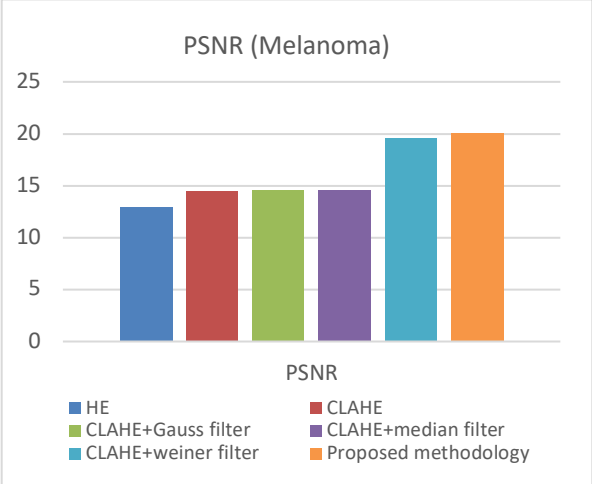
		HE	CLAHE	CLAHE + Gausian	CLAHE + Median	CLAHE + Weiner	Proposed
Entropy	Melanoma	7.9716	7.7972	7.8014	7.8001	7.8040	7.9968
	Naevus	7.9737	7.7622	7.7689	7.7679	7.7730	7.9818
PSNR	Melanoma	12.941	14.502	14.563	14.614	19.601	21.108
	Naevus	12.122	14.095	14.128	14.173	17.162	20.432
FSIM	Melanoma	0.6869	0.5984	0.6033	0.6134	0.6154	0.8278
	Naevus	0.6339	0.5304	0.5345	0.5469	0.5460	0.8122
SRSIM	Melanoma	0.7735	0.7486	0.7537	0.7658	0.7638	0.9355
	Naevus	0.7312	0.7152	0.7195	0.7313	0.7295	0.9195
MAE	Melanoma	16.963	8.6917	8.2360	8.0285	7.9539	4.6756
	Naevus	24.744	13.628	13.166	12.961	12.737	9.7994
UQI	Melanoma	0.8353	0.8065	0.9039	0.8042	0.9015	0.9384
	Naevus	0.8106	0.8223	0.9182	0.8042	0.9154	0.9247



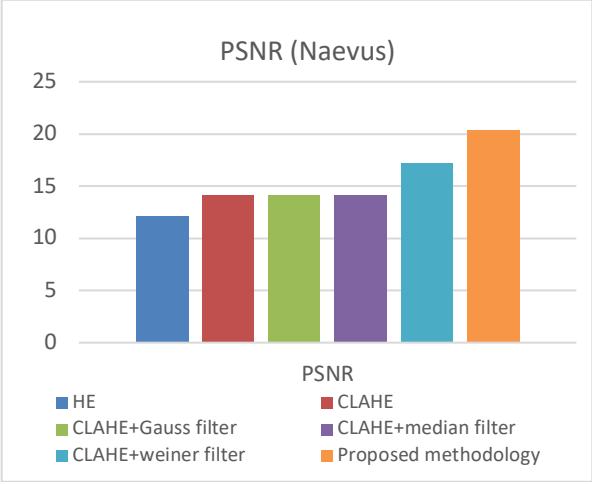
(a)


Entropy (Naevus)
8
7.95
7.9
7.85
7.8
7.75
7.7
7.65
Entropy
HE
CLAHE
CLAHE+Gauss filter
CLAHE+median filter
CLAHE+weiner filter
Proposed methodology

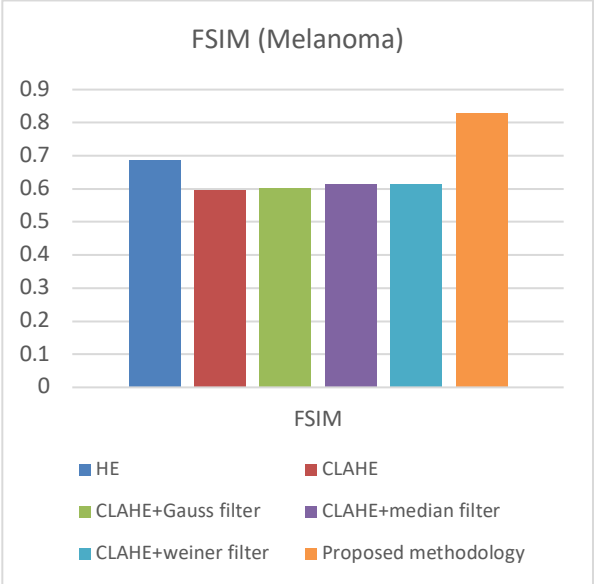
(b)


PSNR (Melanoma)
25
20
15
10
5
0
PSNR
HE
CLAHE
CLAHE+Gauss filter
CLAHE+median filter
CLAHE+weiner filter
Proposed methodology

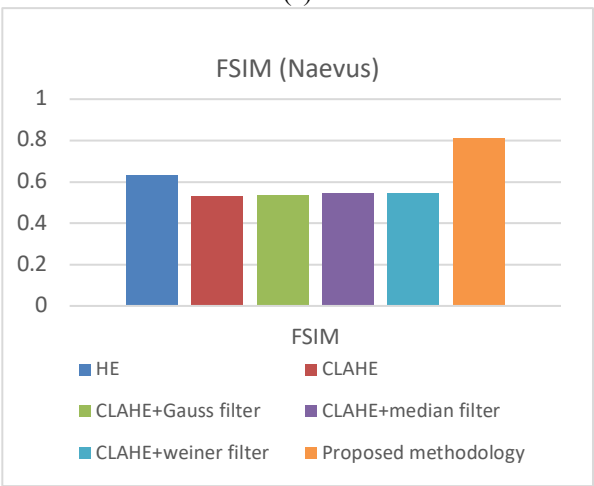
(c)


PSNR (Naevus)
25
20
15
10
5
0
PSNR
HE
CLAHE
CLAHE+Gauss filter
CLAHE+median filter
CLAHE+weiner filter
Proposed methodology

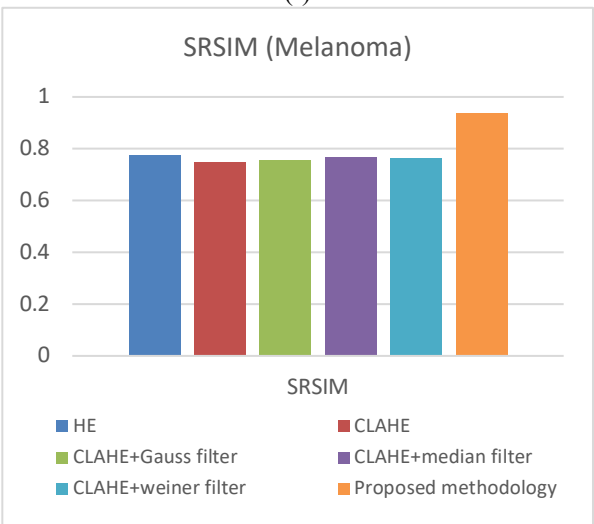
(d)


FSIM (Melanoma)
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
FSIM
HE
CLAHE
CLAHE+Gauss filter
CLAHE+median filter
CLAHE+weiner filter
Proposed methodology

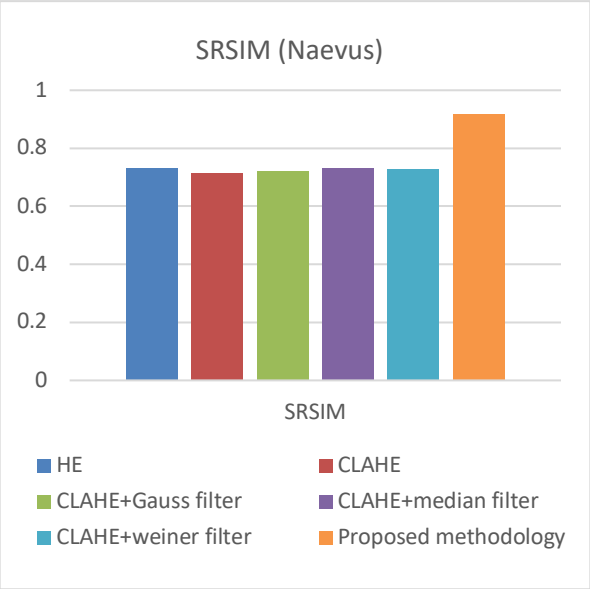
(e)


FSIM (Naevus)
1
0.8
0.6
0.4
0.2
0
FSIM
HE
CLAHE
CLAHE+Gauss filter
CLAHE+median filter
CLAHE+weiner filter
Proposed methodology

(f)


SRSIM (Melanoma)
1
0.8
0.6
0.4
0.2
0
SRSIM
HE
CLAHE
CLAHE+Gauss filter
CLAHE+median filter
CLAHE+weiner filter
Proposed methodology

(g)



(h)

Fig. 3 Graphs for Entropy, PSNR, FSIM and SRSIM

It has been observed from the figure 3, that graphs for Entropy, PSNR, FSIM and SRSIM have maximum values for proposed methodology and the error MAE is found to have minimum value for proposed methodology. All of these indicates the proposed method is providing efficient enhancement as compared to other enhancement methods.

5. Conclusion

In this paper, we have presented an image enhancement framework tailored specifically for skin cancer. The proposed approach addresses the limitations of existing methods by combining robust preprocessing techniques, CLAHE, median filter and log ratio difference.

The key contributions of this work include a method that enhances the visibility of diagnostic features while preserving natural skin tones, an edge-aware filtering technique that reduces noise Extensive experiments on MedNode datasets demonstrated the effectiveness of our method in improving objective image quality metrics and subjective visual assessments compared to state-of-the-art techniques. Moreover, the enhanced images led to significant improvements in the performance parameters for melanoma and naevus images.

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