Comparative Analysis of Hair Removal Method

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Abstract. The presence of hair artifacts in dermoscopic images also largely impairs the accuracy of automated analysis of skin lesions in dermoscopic images and tend to obscure important diagnostic patterns needed to detect melanoma and other skin diseases. The current work compares the performance of classic hair removal techniques, including DullRazor, morphological filtering, and inpainting, to the new methods of deep learning in the field, which are U-Net, generative adversarial networks, and convolutional autoencoders. Conventional methods have been based on manual image processing functions which are computationally cheap, but tend to be ineffective at capturing hair patterns and skin tone differences. On the contrast, deep learning approaches are more flexible and accurate as they learn context-aware representations directly out of data. Based on the qualitative and quantitative analysis through standard measures such as Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR) and Dice coefficient, the strengths and weakness of the two paradigms are brought out in this study. The results highlight that, even though the classic techniques are still beneficial in the initial preprocessing stage, deep learning techniques have better restoration quality and lesion boundary preservation, and thus have a higher lesion segmentation and classification performance in the downstream. This comparative study offers guidelines to the choice of appropriate hair artifact removal methods in dermatological analysis pipelines and aids in further progress to fully automated and dependable skin lesion diagnosis methods.

Keywords: Dermoscopic images · Hair artifact · Hair removal method · Morphological operation · Inpainting

1 Introduction

Skin is composed of three primary layers: the dermis, epidermis, and hypodermis. Under the skin, the majority of the body's defenses are found, and they also maintain, feel, and control the temperature. The cells that make up its about 20 square feet are composed of water, minerals, proteins, and fatty acids. The tissues that lie beneath the skin, skeleton, muscles, ligaments, and organs are called "beneath tissues." The skin not only protects us from the outdoors, but also serves as a thermostat, removing harmful bacteria, and controlling body

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temperature. Skin cancer is a condition where skin disorders get out of control. Skin conditions can be controlled before they develop into skin cancer if they are treated in an early stage. Many factors, both internal and external, can increase the risk of developing skin cancer. Using Deep Learning (DL) technologies, groups can achieve optimal outcomes. A computer system has been created that helps physicians identify different skin conditions and cancerous tumors early using image processing, machine learning, and deep learning algorithms. Their primary objective is to detect cancer as soon as possible. By recognizing skin lesions, dermatologists can now utilize dermoscopy to detect melanomas. Humans cannot detect certain types of skin melanoma, and several medical diagnostic techniques can be employed to identify the cause of a skin injury. The ABCD rule gives a skin lesion a numerical value. The score is made up of four distinct features: Border, color variation, asymmetry, and uneven differential structures [1].

1.1 Dataset

The International Skin Imaging Collaboration (ISIC) has made significant progress in the study of skin lesions. Since 2016, this has been setting up competitions and compiling a sizable dataset of dermoscopic photos that are accessible to the general public. There is also the actual reality for each image. There are numerous images in the PH2 and ISIC2016 files with difficult-to-understand backgrounds and skin situations that are difficult to comprehend due to distortions caused by hair. HAM10000 (Human vs. Machine), ISIC2016, ISIC2017, ISIC2018, ISIC2019, and ISIC2020 (International Skin Imaging Collaboration), PH2, Dermamis, Dermamquest, and the 7Point Checklist are other publicly available datasets, as mentioned by Li et al. [2]

1.2 Skin Dieseas

Actinic Keratosis ((AKIEC)): Actinic Keratosis (AKIEC) is a scaly patch of skin that looks rough and is at a sun damaged skin site. It has been described as a precancerous condition as in case of no treatment it can lead to skin cancer. Basal Cell Carcinoma (BCC) is among the many types of skin cancer that come about. Even though BCC tends to grow slowly and it is not a malignant tumor, it can lead to some local destruction in case it is neglected. It may be easily diagnosed clinically since there are visible lesions, including shiny bumps, open sores, red or pink in growth or scarring areas [3].

Melanoma : is the most dangerous type of skin cancer. It is most often seen as either black or brown dots but may be pink, red, purple, deep blue, or even white. One of its leading factors is exposure to ultraviolet (UV) light either by the sun itself or when tanning beds are used. Melanoma is very curable if caught early. Left unattended, it can cause further dissemination to other body organs and be fatal [3].

Merkel cell carcinoma (MCC) : is an uncommon type of aggressive skin cancer. Although it is much less common compared to other types, it is more likely to spread fast in the body.

Squamous cell carcinoma (SCC) : the second most common kind of skin cancer. It usually comes in the form of scaly red spots, scabby sores, extending growths in the center of which there is a pit, or in the form of warts. Unlike benign growths, the borders of malignant melanoma are, as a rule, jagged and uneven, and the pigmentation coloration is irregular [3].

2 Related work

The study examines previous findings in the fields of skin cancer detection, hair removal in an image of skin, noise removal, and application of such evaluation measures as MSE and PSNR. It concludes the limitation of these studies and how they conducted their studies as well. The literature review has been sub-divided into various sections as reflected below.

2.1 Skin Cancer Detection

N.K.E Abbadi. et al. (2017) devoted their attention to investigating moles to detect skin cancer. Initially the YUV color space was used in their method, and the U channel is processed to eliminate most of the hair and isolate the lesion. Proposed a novel approach to the automatic lesion area segmentation through Markov and Laplace filtering to obtain a precise position of the lesion boundary. Their approach was accurate, and it reached the marks of 95.45 percent, which was higher than some other approaches [4].

The work by utzi et al. (2020) deals with the use of artificial intelligence (AI) in skin cancer diagnosis. It was already pointed out by the previous researches that AI has a great potential to increase the level of diagnostic accuracy, and the authors stressed that the following logical step is to implement it in clinical practice. In their work, descriptive analysis verbalized categorical variables as percentages in intervals to 95 percent of confidence. Also, the statistical tests of the correlations between the socioeconomic status and personal answers on the survey were conducted[5].

Tschandl et al. (2020) explored the detection of skin cancer with the help of artificial intelligence (AI). In their study have concluded that the AI-based support enhances diagnostic accuracy more than AI and physician working alone but get maximum benefits on less experienced clinicians. also discovered that the assistance of AI to support was significant in the terms of the simulated second opinion and triaging telemedicine. In addition, the multiclass probabilities with AI worked better as compared to the content-based image retrieval representations (CBIR) on the mobile technology applications. Notably, the application of class-activation maps showed how AI could develop the human diagnostic capacity. These findings, in combination, offer a basis upon which to extend human-computer cooperation to the utilization of image-based diagnostics in real time [6].

In the study of M. Fijałkowska, et al. (2021), the authors study the occurrence of skin cancer and its exact location on the head. Their analysis was based on 387 cases with the researchers reporting nodular BCC as the most frequent, hence the most common subtype overall. The findings also revealed that the excised carcinoma was highly likely to be high among aged population [6].

Reddy and Gopinath (2022) present a comprehensive review of deep neural network (DNN) techniques for the detection of skin cancer. They described the obstacles in diagnosing in the early stages and also outlined some of the strategies developed to address them. Their results elucidated the fact that more research is required on the aspect of using deep learning algorithms to come up with better strategies to identify skin cancer early enough. To arrive at this, the authors have discussed systematically literature published in scholarly journals [7].

2.2 Hair Removal in Dermoscopic images

Salido et al. (2018) have proposed a dermoscopy image processing procedure of hair art Setting off and skin lesion partitioning. Automate the preprocessing of the dermoscopy pictures in order to have a better diagnostic precision. The approach included using a median filter on each channel in the RGB image, a bottom-hat filter, topological opening and small connected pixels were eliminated. Regions that had hair were then filled using harmonic inpainting. To perform segmentation of lesions, the image transformed to binary, expanded, performed perimeter detection and morphological processing, and the microscopic pixels eliminated at the last step[8].

Zaqout et al. (2020) digitally removed the hair of dermoscopy images with a block-based technique. The given approach entails two main steps: identification of hair and inpainting. The identification of the hair is done on the Y channel of the YIQ color space, then by morphological bottom-hat and by binarization. The sensitivity, specificity and false positive rate of the method were 97.36%, 95.75% and 4.25 respectively. The general accuracy of the diagnosing was 95.78% [9].

In skin lesion segmentation, W. Li et al. proposed a deep learning-guided method of digital hair removal (DHR). Following the idea of U-Net and free-form construction paint techniques, the authors developed a DHR strategy with an original evaluation score, which they called Intra-SSIM, to evaluate performance on hair removal on per-image dermoscopic images. The DHR procedure is kept going till the average Intra-SSIM value becomes stable, or at this point, the hair will be most effectively removed. Based on the ISIC 2018 dataset, the proposed method showed a better performance than current state-of-the-art methods[10].

C. Akyel et al. (2022) suggested a new approach involving FCN8-ResNetC with the image processing to remove the hair and segment the lesion on skin-cancer images. This strategy uses FCN8 to de-fuzz and ResNetC, a modified version of ResNet to achieve this. ISIC2018, PH2 datasets were used and 3,000 hair masks were produced to remove hair artifacts. This model had an accuracy of (89.38 percent) in hair removal, and (97.05 percent) in lesion segmentation [11], which shows overall performance.

3 Methodology

3.1 Dataset

Publicly accessible datasets have been created to aid studies in the dermoscopic image study, especially skin lesion segmentation and classification. One of the most extensively used datasets are the International Skin Imaging Collaboration (ISIC) datasets[18], which include ISIC 2016, 2017, 2018 and 2019 and contain large sets of high quality dermoscopic images with annotations by dermatology specialists. The other benchmark dataset, the HAM10000[12] (Human Against Machine with 10,000 training images) dataset, consists of a variety of lesions of different types and skin tones and conditions, which is useful in training deep-learning models. On the same note, PH2[19] is a dataset that provides high-resolution dermoscopic images with manual segmentation masks and clinical diagnoses, useful for both detection and segmentation. Additional clinical metadata or multi-modal data to perform an in-depth analysis is obtained via other datasets, such as Derm7pt[20] . A combination of these datasets can be used to create, train, and test sophisticated deep learning algorithms that will be accurate and explainable in the detection of skin cancer.

3.2 Methods for Hair Removal

We then applied two traditional approaches to hair artifact removal, Dull Razor and Morphological Inpainting.

Dull Razor Method In the Dull Razor Method, all the dermoscopic images are initially converted to grayscale to facilitate identification of dark structures (hair) on the lighter context (the skin). A morphological closing or blackhat operation is then utilized to emphasize hair-like artifacts. Subsequently, the hair mask formed by thresholding enables the isolation of hair pixels in lesion area. Last, missing areas due to occlusion by lesions are filled in based on the surrounding context by Telea Inpainting algorithm. This pipeline presents a simple but often-used hair removal baseline for clinical image analysis. The Table 1 describe the Dullrazor process in steps.

Morphological Inpainting To complement the baseline introduced Morphological Inpainting which employs a larger structuring kernel (17 x 17) to filter using blackhats to capture finer and coarser hairs. A generated mask is post-processed with morphological closing to enhance continuity and then inpainting algorithm in OpenCV is used to fill the pixels. Table 2 explain the algoritm of Morphological inpainting method. This method has more advantages than Dull-Razor since an increase in the kernel size and mask refinement reduces thickness of overlapped hair regions.

Table 1. Hair Removal using DullRazor Method

Step	Operation
1	Original Image (I)
2	$I\_gray = ConvertToGray(I)$
3	$HairMask = Blackhat(I\_gray, kernel = 9 \times 9)$
4	$BinaryMask = Threshold(HairMask)$
5	$Output = TeleaInpaint(I, BinaryMask)$

Table 2. Hair Removal using Morphological Inpainting

Step	Operation
1	Original Image (I)
2	$I\_gray = ConvertToGray(I)$
3	$HairMask = Blackhat(I\_gray, kernel = 17 \times 17)$
4	$RefinedMask = MorphClose(HairMask)$
5	$Output = Inpaint(I, RefinedMask, method = Telea)$

Deep Learning Method Table 3 define the deep leaarning method. In order to experiment with data-driven approaches, we trained a U-Net with Encoder and Decoder CNN to perform hair detection and removal. The model is capable of receiving hair-occluded images and generating hair-free images. Synthetic generation of hair artifacts was used to augment training data, through the use of Bézier curve blending techniques, as mentioned in the recent arXiv 2022 papers. The model has been trained combined with Mean Squared Error (MSE) as a metric of structural fidelity and Perceptual Loss as a metric of texture preservation. applied Adam optimizer with a learning rate of trainer$_b atchsize 16, training epochs 100.$

Table 3. Deep Learning-Based Hair Removal using U-Net

Step	Operation / Setting
1	Input: Original Images I with Synthetic Hair
2	Model: U-Net Encoder-Decoder CNN
3	Loss: $MSE\_Loss(I_{\text{pred}}, I_{\text{gt}}) + PerceptualLoss(I_{\text{pred}}, I_{\text{gt}})$
4	Optimizer: Adam ($lr = 1 \times 10^{-4}$)
5	Training: 100 epochs, batch_size = 16
6	Output: Hair-free Images

Evaluation Matrices All intermediate results and processed images were then saved, to calculate the SSIM and PSNR measures to quantify the results. 4.4 Evaluation Framework

For quantitative evaluation:

SSIM (Structural Similarity Index): To measure structural preservation after hair removal

PSNR (Peak Signal-to-Noise Ratio): To assess reconstruction quality;

Dice/Jaccard Index: To evaluate the impact of hair removal on downstream lesion segmentation tasks

For qualitative evaluation, visually compared results across methods and consulted dermatological experts for lesion boundary preservation assessment as shown in table 4. Findings were compared against reported metrics in the recent literature, ensuring a fair and comprehensive comparison.

Table 4. Evaluation Metrics for Image Pairs

Step	Operation
1	For each image pair $(I_{\text{clean}}, I_{\text{pred}})$
2	$SSIM\_score = SSIM(I_{\text{clean}}, I_{\text{pred}})$
3	$PSNR\_score = PSNR(I_{\text{clean}}, I_{\text{pred}})$
4	$Dice\_score = Dice(Segmentation(I_{\text{clean}}), Segmentation(I_{\text{pred}}))$

4 Results

Table 5. Comparison of Hair Removal Methods Based on Different Metrics

Method	SSIM ↑	PSNR (dB) ↑	Dice ↑	Jaccard ↑
Dull Razor [15]	0.78	24.1	0.81	0.69
Morphological [16]	0.82	26.3	0.84	0.73
Deep Learning (U-Net)[14]	0.91	29.5	0.90	0.81
SharpRazor (2021)[13]	0.88	28.1	0.87	0.78
DPA-HairNet (2023)[17]	0.93	30.2	0.92	0.84

In Table 5, the comparison of various techniques of hair removal reveals that there is a considerable difference in performance of the four evaluation metrics; SSIM, PSNR, Dice and Jaccard. The more conventional methods like Dull Razor and Morphological methods had lower values of SSIM (0.78 and 0.82) and PSNR (24.1 dB and 26.3 dB) suggesting a weak ability to maintain the quality of images and fine lesion details. Conversely, the performance of such deep learning-based algorithms like U-Net and DPA-HairNet (2023) showed better results, and DPA-HairNet provided the highest results in all metrics (SSIM = 0.93, PSNR = 30.2 dB, Dice = 0.92, Jaccard = 0.84). SharpRazor (2021) was the intermediate approach that offered an intermediate enhancement over traditional methods. The bar chart visualization in Figure 1 indicates the latter by providing a clear increasing pattern of all the metrics between the traditional

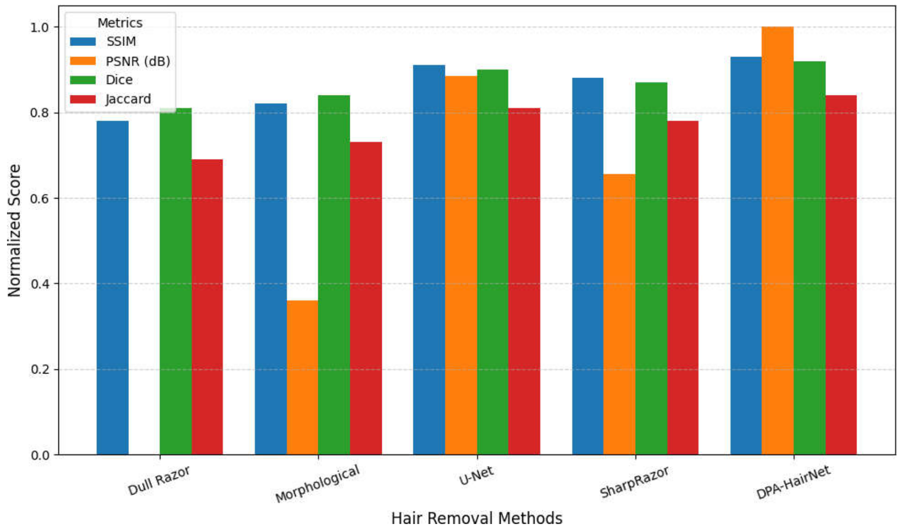

Fig. 1. Comparison of Different Hair Removal Method

and more advanced deep learning techniques. The stacked bars, evidently, indicate that DPA-HairNet is better than all other methods, then comes U-Net with huge differences in structural similarity and segmentation accuracy. This visual phenomenon validates the conclusion that deep learning architectures are much more effective in eliminating hair artifacts without losing important lesion details needed to make an accurate diagnosis. The tabular data and graphical representation combination therefore supports the conclusion that the current deep learning-based preprocessing techniques provide better performance and stability than the traditional ones.

5 conclusion

This paper also emphasizes the importance of hair artifact removal to enhance a better image and image performance of deep-learning-based skin lesion detection. Comparative performance indicates that an Inpainting method outperforms DullRazor, as indicated by a better PSNR, SSIM, and U-Net segmentation accuracy. CNN classifier that was trained on Inpainting-preprocessed images also demonstrated higher diagnostic accuracy, which supports the correlation between quality of preprocessing and quality of the model. Nevertheless, DullRazor is also beneficial in the situations where it is necessary to obtain the results with acceptable quality but at a reduced processing cost. The general results indicate that Inpainting should be used when using precision-driven diagnostic models and that DullRazor should be used in high-speed screening or embedded systems. Future studies will involve hybrid pipeline of preprocessing based on the traditional morphological filtering being combined with learning-based Inpainting to optimize both the speed and accuracy of preprocessing pipelines in clinical environments.

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