An Effective Method for Detecting and Removing Hair Artifacts in Dermoscopic Images

Gulmirzaeva Guzal
Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Tashkent, Uzbekistan

Rajabov Jamshid
Karakalpak State University, Nukus, Uzbekistan

Received: 28 Mar 2026 | Received Revised Version: 24 Apr 2026 | Accepted: 20 May 2026 | Published:06 June 2026

Volume 08 Issue 06 2026 | Crossref DOI: 10.37547/tajet/Volume08Issue06-19

Abstract

Hair artifacts in dermoscopic images distort the boundaries of skin lesions, alter texture features, and reduce the accuracy of automatic segmentation and classification systems. In this paper, a method based on morphological Black-hat filtering, probabilistic Hough transform, and local median interpolation is proposed to remove hair artifacts from dermoscopic images. The proposed method is computationally simple and CPU-efficient, and it was evaluated using PSNR and SSIM metrics. Experimental results show that this method improves the visual quality of dermoscopic images, removes hair artifacts while preserving important diagnostic features of the dermoscopic image, and is a suitable preprocessing method for the next segmentation step.

Keywords: Dermoscopic image, hair artifact, Black-hat, Hough transform, median interpolation, image preprocessing.

Cite This Article: Gulmirzaeva Guzal, & Rajabov Jamshid. (2026). An Effective Method for Detecting and Removing Hair Artifacts in Dermoscopic Images. The American Journal of Engineering and Technology, 8(06), 214–218. https://doi.org/10.37547/tajet/Volume08Issue06-19

1. Introduction

Nowadays, automated segmentation and classification systems using medical images, especially dermoscopic images, are widely developed, as they help clinical decision-making and reduce errors due to the human factor. However, the presence of hair artifacts in dermoscopic images obscures important features and distorts internal pigmentation and texture features. As a result, the efficiency of automated diagnosis of melanoma and other skin lesions decreases. [1] [2]. Therefore, hair detection and removal is one of the important issues in pre-processing medical images [3]. Existing hair removal should not only eliminate image artifacts but also preserve the diagnostically important features of the lesion, such as its border, pigmentation, and texture. Existing approaches, based on traditional image processing methods such as morphological operators, thresholding, Hough transform, and classical inpainting, require relatively low computational resources, are simple and straightforward to implement, and can be used without a large database. In such methods, hairs are identified using morphological methods and areas covered by hairs are restored using inpainting methods [4]. For example, Telea uses black-hat morphological operations in conjunction with inpainting to effectively remove hair artifacts and preserve diagnostically important features [5]. However, these methods often have difficulty adapting to changes in feather thickness, color, and background complexity [6], which necessitates further improvements in feather detection and inpainting strategies [7]. In addition to classical approaches, deep learning-based models are also being used to remove hair from images. However, in some cases, they can also incorrectly remove dark structures within the lesion or artificially smooth the restored areas, affecting the authenticity of the image [8] [9]. Also, while Deep Learning-based approaches are more flexible than traditional methods, they require large amounts of data and computational resources.

To overcome these limitations, this study proposes a hybrid approach based on the probabilistic Hough transform to detect linear features of hair structures. In addition, a statistical verification step is applied to reduce false detections by analysing the pixel intensity distribution and structural continuity of the detected segments. The proposed method preserves important diagnostic features of the lesion while increasing the stability of the hair removal process, and as a result, significantly improves the reliability of dermoscopic image analysis.

Related work

An analysis of the literature in this area shows that existing methods for removing hair artifacts from dermoscopic images can be conditionally divided into three main approaches: classical morphological methods, geometric and block analysis methods, and approaches based on deep learning. One of the earliest and most widespread classical morphological methods is the DullRazor algorithm [10], which is based on hair detection and interpolation using morphological operations. [11] The proposed approach uses morphological closing operation combined with pixel interpolation and median filter to reduce noise. However, these methods are mainly effective in detecting thick and dark hair, and may cause errors in detecting thin or light hair.

To overcome these limitations of classical approaches, other studies have applied morphological bottom-hat operations on the Y-channel of the YIQ color space, followed by hair detection through binarization and image reconstruction through block-based pixel replacement (inpainting) strategies [12]. The effectiveness of these methods is usually evaluated based on the preservation of lesion features and real-time computational efficiency. Approaches have also been developed to eliminate dark lines and specular reflections through the use of adaptive and iterative weighted median filters, Gaussian derivatives, and pattern-based object removal methods [13][14]. More advanced methods integrate Black-hat morphological operations with the Telea inpainting method, ensuring efficient separation and removal of hair artifacts while preserving important structural features of the lesion [15]. In addition, inpainting methods based on total variation have been proposed as an effective solution for improving dermoscopic images. [5]. However, these approaches are often limited by computational complexity on high-resolution images and problems with over-smoothing of subtle clinical features.

Unlike classical methods, geometric and block analysis approaches consider hair in a dermoscopic image not as a simple object, but as a set of mathematical lines [16]. These methods divide the image into blocks and model the complex curvatures of hair as line segments, resulting in a more geometrically accurate distinction between hair and skin lesions. However, detecting hair structures of different orientations and thicknesses remains a challenge [17] [18] [19].

In recent years, deep learning-based approaches, including advanced encoder-decoder architectures, have shown high performance in segmenting and removing artifacts from dermoscopic images [20]. These methods analyze hair as a complex semantic layer, providing high-accuracy results. However, such models require large datasets and high computational resources, making them difficult to apply in resource-constrained clinical settings [22]. Given these limitations, the proposed morphological-geometric approach in this study combines the simplicity of classical methods with the accuracy of geometric methods. This approach serves to increase the overall accuracy of subsequent segmentation and classification processes by clearly distinguishing hair artifacts from real lesion features, and allows for effective application even in conditions with limited computational resources.

2. Methodology

In this work, a multi-step method based on morphological, geometric and statistical analysis is proposed to remove hair artifacts from dermoscopic images (Fig. 1). The main goal of the proposed approach is to detect dark linear structures characteristic of hair, distinguish them from significant pigmented areas of the lesion, and restore the image while preserving natural features. First, the input image is converted from RGB space to grayscale. This step simplifies the computation and helps to more accurately separate intensity-based features. In the next step, a morphological Black-Hat transformation is applied to enhance hair fibers. This operation calculates the difference between the morphological closure result and the original grayscale image:

$$I_{bh} = (I_{gray} \cdot S) - I_{gray}$$

where I_{gray} - is gray image, S - is the structural element, $\cdot$ is the morphological closure operation. As a result, dark and thin objects like hair appear more clearly.

Then, binary thresholding is applied to the Black-Hat result to generate an initial hair candidate mask. However, not all detected objects may be hair at this stage. Therefore, in the next stage, segments with linear geometry are extracted using the Probabilistic Hough Transform. This approach is used to detect fine and directional structures characteristic of hair. The resulting binary mask and geometric detection results are combined to form a hair mask. Then, a statistical protection step is performed to prevent the central lesion area from being incorrectly deleted. In this step, the distribution of the mask pixels across the image and their location relative to the center are evaluated. If the detected objects are very densely located in the center, they are interpreted as lesion pigmentation and protected, rather than hair.

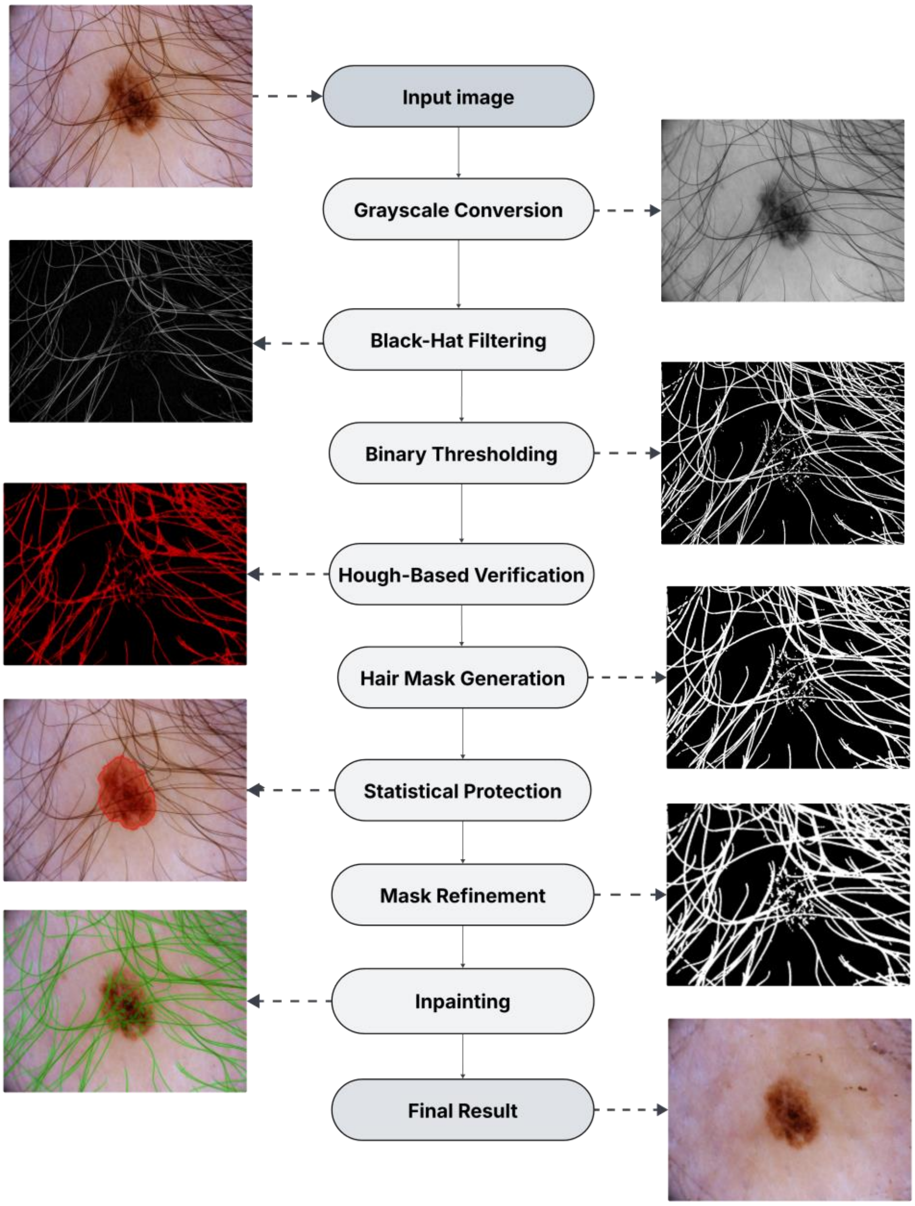

Figure 1. Flowchart of morphological-based hair artifact removal from dermoscopic images.

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In the next step, the mask is morphologically improved, i.e., the broken segments are merged and the contours are rounded. Finally, the hair artifacts under the validated mask are restored using the local median interpolation algorithm.

$$I'(x, y) = median(N(x, y))$$

In this method, each pixel in the mask is filled with the average value of its surrounding neighboring pixels. Thus, the proposed method, combining Black-Hat filtering, Hough-based geometric inspection, statistical protection, and inpainting steps, allows for effective removal of hair artifacts from dermoscopic images while preserving important diagnostic features.

3. Results

The results showed that the proposed method performed better in terms of PSNR and SSIM values when compared to the DullRazor, SharpRazor, and Xie methods (Table 1). This indicates that the method not only effectively removes hair artifacts, but also better preserves important structural and diagnostic features of the dermoscopic image.

Table 1. Comparison of calculation results (on the PH2 dataset)

Methods	*PSNR*	*SIM*
DullRazor[10]	29.15	89.16
SharpRazor[6]	30.67	89.97
Xie [17]	31.09	89.87
Proposed model	31.96	91.84

In addition, the method has a short computation time and does not require large computational power or complex hardware resources. Therefore, the proposed approach was evaluated as a practical, resource-efficient, and stable method.

4.Conclusion

In conclusion, the proposed method has shown effective results in removing hair artifacts from dermoscopic images. The algorithm results in an image with relatively preserved skin texture and free of hair artifacts. This methodology is considered a simple, understandable and practical solution for preprocessing dermoscopic images for subsequent segmentation and classification stages.

References

1. A. R.P. and J. Zacharias, ‘Semantic segmentation in skin surface microscopic images with artifacts removal’, Computers in Biology and Medicine, vol. 180, p. 108975, Sep. 2024, doi: 10.1016/j.compbiomed.2024.108975.
2. Z. Wang et al., ‘Influence of hair presence on dermoscopic image analysis by AI in skin lesion diagnosis’, Computers in Biology and Medicine, vol. 183, p. 109335, Dec. 2024, doi: 10.1016/j.compbiomed.2024.109335.
3. C. F. O.- Blandón, E. Restrepo-Parra, J. Rojas, and F. J. Ayerbe, ‘Multiscale Morphological Reconstruction for Hair Removal in Dermoscopy Images’, Modern Applied Science, vol. 12, no. 12, pp. 90–90, Nov. 2018, doi: 10.5539/mas.v12n12p90.
4. A. S. Ashour et al., ‘Cascaded Hough Transform-Based Hair Mask Generation and Harmonic Inpainting for Automated Hair Removal from Dermoscopy Images’, Diagnostics, vol. 12, no. 12, p. 3040, Dec. 2022, doi: 10.3390/diagnostics12123040.
5. A. H. Khan, D. N. F. A. Iskandar, J. F. Al-Asad, and S. El-Nakla, ‘Classification of Skin Lesion with Hair and Artifacts Removal using Black-hat Morphology and Total Variation’, International Journal of Computing and Digital Systems, vol. 10, no. 1, pp. 597–604, May 2021, doi: 10.12785/ijcds/100157.
6. R. Kasmi et al., ‘SharpRazor: Automatic removal of hair and ruler marks from dermoscopy images’, Skin Research and Technology, vol. 29, no. 4, Mar. 2023, doi: 10.1111/srt.13203.

7. D. Kang, S. Kim, and S. Park, ‘Flow-guided hair removal for automated skin lesion identification’, Multimedia Tools and Applications, vol. 77, no. 8, pp. 9897–9908, Jan. 2018, doi: 10.1007/s11042-018-5672-7.
8. Ç. Suiçmez, H. Tolga Kahraman, A. Suiçmez, C. Yılmaz, and F. Balcı, ‘Detection of melanoma with hybrid learning method by removing hair from dermoscopic images using image processing techniques and wavelet transform’, Biomedical Signal Processing and Control, vol. 84, p. 104729, Jul. 2023, doi: 10.1016/j.bspc.2023.104729.
9. A. Shahzaib, A. B. Siddiqui, N. Anjum, M. U. Rehman, and N. Ramzan, ‘Hair removal and lesion segmentation of dermoscopic images for classification of skin cancer using deep neural networks’, Egyptian Informatics Journal, vol. 32, p. 100844, Dec. 2025, doi: 10.1016/j.eij.2025.100844.
10. T. Lee, V. Ng, R. Gallagher, A. Coldman, and D. McLean, ‘Dullrazor®: A software approach to hair removal from images’, Computers in Biology and Medicine, vol. 27, no. 6, pp. 533–543, Nov. 1997, doi: 10.1016/S0010-4825(97)00020-6.
11. C. Sagar and L. M. Saini, ‘Color channel based segmentation of skin lesion from clinical images for the detection of melanoma’, in 2016 IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), Delhi, India: IEEE, Jul. 2016, pp. 1–5. doi: 10.1109/ICPEICES.2016.7853624.
12. I. Zaqout, ‘An Efficient Block-Based Algorithm for Hair Removal in Dermoscopic Images’, in Computer Methods and Programs in Biomedical Signal and Image Processing, L. Wang, Ed., IntechOpen, 2020. doi: 10.5772/intechopen.80024.
13. K. Delibasis, K. Moutselos, E. Vorgiazidou, and I. Maglogiannis, ‘Automated hair removal in dermoscopy images using shallow and deep learning neural architectures’, Computer Methods and Programs in Biomedicine Update, vol. 4, p. 100109, 2023, doi: 10.1016/j.cmpbup.2023.100109.
14. Q. Abbas, M. E. Celebi, and I. F. García, ‘Hair removal methods: A comparative study for dermoscopy images’, Biomedical Signal Processing and Control, vol. 6, no. 4, pp. 395–404, Oct. 2011, doi: 10.1016/j.bspc.2011.01.003.
15. A. S. Al-Waisy, S. Al-Fahdawi, M. Khalaf, M. A. Mohammed, B. Al-Attar, and M. N. Al-Andoli, ‘A deep learning framework for automated early diagnosis and classification of skin cancer lesions in dermoscopy images’, Scientific Reports, vol. 15, no. 1, Aug. 2025, doi: 10.1038/s41598-025-15655-9.
16. S. Nazari and R. García, ‘Automatic Skin Cancer Detection Using Clinical Images: A Comprehensive Review’, Life, vol. 13, no. 11. Multidisciplinary Digital Publishing Institute, pp. 2123–2123, Oct. 2023. doi: 10.3390/life13112123.
17. F. Xie, S. Qin, Z. Jiang, and R. Meng, ‘PDE-based unsupervised repair of hair-occluded information in dermoscopy images of melanoma’, Computerized Medical Imaging and Graphics, vol. 33, no. 4, pp. 275–282, Mar. 2009, doi: 10.1016/j.compmedimag.2009.01.003.
18. ‘From Dermoscopy to Mobile Teledermatology’, in CRC Press eBooks, Informa, 2015, pp. 401–434. doi: 10.1201/b19107-16.
19. R. B. Oliveira, M. Filho, Z. Ma, J. P. Papa, A. S. Pereira, and J. M. R. S. Tavares, ‘Computational methods for the image segmentation of pigmented skin lesions: A review’, Computer Methods and Programs in Biomedicine, vol. 131. Elsevier BV, pp. 127–141, Apr. 2016. doi: 10.1016/j.cmpb.2016.03.032.
20. W. El-Shafai, I. A. El-Fattah, and T. E. Taha, ‘Deep learning-based hair removal for improved diagnostics of skin diseases’, Multimedia Tools and Applications, vol. 83, no. 9, pp. 27331–27355, Sep. 2023, doi: 10.1007/s11042-023-16646-6.
21. D. Bardou et al., ‘A Review of Automatic Hair Removal in Dermoscopy Images: From Image Processing to Deep Learning’, J Digit Imaging. Inform. med., Apr. 2026, doi: 10.1007/s10278-026-01950-y.
22. L. Jütte, H. Patel, and B. Roth, ‘Advancing dermoscopy through a synthetic hair benchmark dataset and deep learning-based hair removal’, Journal of Biomedical Optics, vol. 29, no. 11, pp. 116003–116003, Nov. 2024, doi: 10.1117/1.jbo.29.11.116003.