Made available by Hasselt University Library in https://documentserver.uhasselt.be

Utilizing Image Processing Techniques for Wound Management and Evaluation in Clinical Practice: Establishing the Feasibility of Implementing Artificial Intelligence in Routine Wound Care

Peer-reviewed author version

Dabas, Mai; Kapp, Suzanne & GEFEN, Amit (2025) Utilizing Image Processing Techniques for Wound Management and Evaluation in Clinical Practice: Establishing the Feasibility of Implementing Artificial Intelligence in Routine Wound Care. In: Advances in skin & wound care, 38 (1) , p. 31 -39.

DOI: 10.1097/ASW.0000000000000246
Handle: http://hdl.handle.net/1942/45287

Dabas M, Kapp S, Gefen A. Utilizing Image Processing Techniques for Wound Management and Evaluation in Clinical Practice: Establishing the Feasibility of Implementing Artificial Intelligence in Routine Wound Care. Adv Skin Wound Care. 2025 Jan-Feb 01;38(1):31-39. doi: 10.1097/ASW.0000000000000246.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

Utilizing image processing techniques for wound management and evaluation in clinical practice: Establishing the feasibility of implementing artificial intelligence in routine wound care

Mai Dabas, MSc student, Department of Biomedical Engineering, Faculty of Engineering, Tel Aviv University, Tel Aviv, Israel.

Suzanne Kapp, PhD, RN, BN. Clinical Associate Professor, School of Health Sciences, Faculty of Medicine, Dentistry and Health Sciences, Department of Nursing, The University of Melbourne, Melbourne, Australia. National Manager Wound Prevention and Management, Regis Aged Care, Camberwell, Victoria, Australia.

Amit Gefen, PhD, Professor of Biomedical Engineering, The Herbert J. Berman Chair in Vascular Bioengineering, Department of Biomedical Engineering, Faculty of Engineering, Tel Aviv University, Tel Aviv, Israel; Skin Integrity Research Group (SKINT), University Centre for Nursing and Midwifery, Department of Public Health and Primary Care, Ghent University, Ghent, Belgium; Department of Mathematics and Statistics, Faculty of Sciences, Hasselt University, Hasselt, Belgium.

Acknowledgements:

This work was supported by a competitive grant from the Victorian Medical Research Acceleration Fund, with funding co-contribution from the Department of Nursing at the University of Melbourne, the Melbourne Academic Centre for Health, and Mölnlycke Health Care. This work was also partially supported by the Israeli Ministry of Science & Technology (Medical Devices Program Grant no. 3-17421, awarded to Professor Amit Gefen in 2020). The authors would like to thank Ms. Carla Bondini for her assistance with data collection and management for this study and to Mr. Daniel Kapp for proof-reading the manuscript.

Dabas M, Kapp S, Gefen A. Utilizing Image Processing Techniques for Wound Management and Evaluation in Clinical Practice: Establishing the Feasibility of Implementing Artificial Intelligence in Routine Wound Care. Adv Skin Wound Care. 2025 Jan-Feb 01;38(1):31-39. doi: 10.1097/ASW.0000000000000246.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

Abstract

Objective

Accurate determination of wound size and healing supports decision making regarding treatment and is essential to successful outcomes. The aim of this study was to develop a generalizable and accurate method for automatically analyzing wound images captured in clinical practice and extracting key wound characteristics such as surface area measurement.

Methods

We employed image processing techniques to create a robust algorithm for segmenting pressure ulcers/injuries from digital images captured by nurses during clinical practice. The algorithm also measured the real-world wound surface area. We utilized the Hue-Saturation-Value color space to analyze red color values and to detect and segment the wound region within the entire image. To assess the accuracy of the algorithm's wound segmentation, we compared the results against wound image annotations.

Results

The algorithm performed impressively, achieving an Intersection over Union score of up to 0.85 and 100% intersection with the annotations. The algorithm effectively analyzed wound images obtained during clinical practice and accurately extracted the surface area of the documented pressure ulcers/injuries. These results suggest the feasibility and applicability of our methodology.

Conclusions

Our innovative approach for visual assessment of chronic wounds highlights the potential of computerized wound analysis in clinical practice. By leveraging advanced computational techniques, healthcare providers can gain valuable insights into wound progression, enabling more accurate assessments to support their decision making.

Keywords: Artificial intelligence, Chronic wounds, Image processing, Pressure ulcer/injury prevention., Visual assessment, Wound evaluation.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

Introduction

Chronic wounds, such as pressure ulcers/injuries (PUs/PIs), venous leg ulcers and diabetes-related foot ulcers are wounds that fail to progress through an orderly and timely reparation, often due to a stall in the inflammatory phase of healing.[1–3] Such wounds affect the health and quality of life of 1-2% of the population worldwide.[4] Approximately 6.7 million people in the US are affected at an annual cost of 20$ billion, and the amount of cases is expected to grow more than 2%, according to the Mission Regional Medical Center.[3,5,6]

Focusing on PUs/PIs, initial cell and tissue damage is escalated by inflammatory edema which raises the interstitial tissue pressures in tissue regions sandwiched between rigid skeletal structures and a support surface (or a medical device), thus progressively worsening the state of cell deformations and lowering the available vascular supply and lymphatic function.[7] When edema, characterized by tissue swelling and inflammation, persists longer than usual (as in an acute wound), this might indicate that the wound has transitioned into a chronic state.[3] Therefore, the detection and consistent documentation of edema or visible redness in the affected area and the surrounding tissue over time is an important indicator for assessing the development and status of chronic wounds.[3,8]

A key feature of chronic wound evaluation is tracking the progress of the wound toward healing.[9] To do so, tracking the changes in wound surface area over time and calculating healing rate is essential.[9] According to the Guidelines for the Treatment of Diabetic Ulcers [8] and Pressure Ulcers,[10] the wound should undergo an ongoing assessment to evaluate wound healing and to determine whether the treatment is optimal. As evidenced in previously published studies and as pointed out by the aforementioned guideline, percent change in ulcer area over four weeks of treatment is a good indicator of the effectiveness of the therapy and the healing potential of the wound.[8,10–12] The presence of infection and biofilm is known to delay healing and there is emerging evidence that slough may be a biomarker for the healing potential[13] Nonetheless, an accurate, consistent measurement of the wound surface area over time is a critical component of evaluation of wound status.

The traditional assessment of wound surface area is accomplished by manual measurement of the wound width and length using a simple tape measure or by taking an acetate tracing of the wound perimeter and tissue types within.[9] Although these measurements can be performed

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

rapidly, they are subject to inaccuracies and measuring errors, especially in the case of irregular shaped wounds.[14–18]

An emerging methodology for improving wound care is the implementation of computerized machine learning algorithms to support the diagnosis of acute and chronic wounds. Adopting artificial intelligence (AI) technologies has the potential to enable nurses and other healthcare professionals to deliver advanced and improved wound assessment to their patients and allocate their time more efficiently.

Most of the previously published methodologies regarding the implementation of AI in wound care were applied on datasets acquired under controlled laboratory conditions or by a research group.[19] In practice, healthcare providers struggle to systematically collect such image data [20] and most of these methodologies do not apply or do not perform adequately when implemented in real-world conditions.[21–23]

The goal of this research was to establish feasibility for developing a generalizable, robust, sufficiently accurate methodology implemented in software to detect and segment chronic wounds from images captured by nurses in a clinical setting, by utilizing red color values as indicators of edema. Furthermore, we sought to automatically extract the wound surface area measurement from the segmented images, facilitating faster calculation. The role of AI in our current work was to develop a robust, generalizable method for automatically analyzing and extracting key wound characteristics, in particular surface area measurements, from wound images captured routinely in clinical practice, using common smartphones or tablets, based on advanced image processing techniques and a computational algorithm. The method described here improves the efficiency of chronic wound assessments without requiring any special hardware, i.e., dedicated, commercial wound assessment cameras (which are typically costly and necessitate maintenance, potential repairs and technical support). An important contribution of this study is therefore in increasing the accessibility to advanced wound care technology for healthcare professionals, including those who work in remote settings, supporting them in making informed clinical decisions.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

Methods

The wound images used in this project arose from aged care residents who had PIs and who were participants of the current research project. The project involved the nurses who usually cared for residents taking wound images at weekly intervals. This occurred within a feasibility study and a pilot RCT, which evaluated remote expert wound nurse consultations for PI management. Ethics approval to conduct the project, and this study specifically, was obtained from the Office of Research Ethics and Integrity of the [[REDACTED FOR PEER REVIEW]] (Reference Number: 2021-22205-22028-3).

Nurses were trained to take quality wound images according to an imaging protocol which was developed by the research team to meet local requirements as detailed in **Appendix A1** (and depicted in **Figure 1**). The protocol reinforced key messages regarding focus, lighting, angle of the camera with respect to the wound surface, distance of the camera from the wound as well as privacy and confidentiality requirements. Images included a green dot sticker (placed next to the wound by the nurses) serving as a known dimensional scale reference.[1] This was the only part of the imaging process that was not usual practice.

All images were taken by the nurses who provided the wound treatment. Images were taken with either a digital camera, iPad, or other mobile computing device. A subset of 22 images was selected from the database by the research group to form a representative image group for segmentation evaluation. The selected images underwent manual annotation by an advanced practice wound nurse who worked on the project, was experienced in wound imaging and measurement, and who had consulted with the treating nurses and participants regarding their PU/PI management. The annotator marked the location and perimeter of the wound (or areas of the wound) in each image. A senior clinical expert in wound care (author SK) conducted a cross-check of all image annotations to confirm the accuracy and quality of the annotations. Annotating wound edges is a commonly employed process in clinical settings, for example, using a tracing sheet printed with 1 cm grid lines[24]. With this approach, a clinician can

[1] The green dot sticker serves as a known scale reference to facilitate accurate measurement of the surface area of examined wounds. By placing the sticker next to the wound, it provides a consistent size reference for the camera of the smartphone or tablet, enabling the conversion from image scale (pixels) to real-world scale (centimetres) during the image analysis process. Using either a physical item (such as stickers) or projected laser light dots to dimensionally scale measurements in a wound image processing is usual practice (of note, the objective here was to use common smartphones or tablets which do not project laser). In principle, it does not matter what the specific object is as long as it has a known size, be that a ruler with measurements noted or a circle with a known diameter.

(manually) quickly sum the 1 cm grid boxes to evaluate the surface area of the examined wound. Inter- and intra-rater reliability of wound annotations are known to be high among expert clinicians and the accuracy of annotations is greater for relatively large wounds[25]; both of these conditions were met in our study and we therefore expect any discrepancy in annotation to have been minimized. All images were securely transferred to the research team for use in the study. We excluded exceptionally poor images judged to be useless in clinical practice and we would select not to use them for evaluation in usual care.

Patient characteristics and the image database

Participant information was provided with the images, specifically the participants age, gender, ethnicity, skin tone (Fitzpatrick Scale), [26] PI stage in accordance to the Pressure Injury Staging System of the National Pressure Injury Advisory Panel (NPIAP),[27] anatomical location and PI start date.

Image processing and data analysis

Due to a wide range of factors affecting image quality (such as acquisition conditions, distance from the target, and other parameters) initial processing steps were applied to all images to create a more consistent and uniform image database. Firstly, the image size was adjusted to 240x240 pixels to ensure consistency and optimize disk memory usage. Secondly, glare was eliminated from the images using an inpainting technique, where the value of the glared pixels was replaced with the value of their neighboring pixels.[28] This feature was applied only locally and to small numbers of pixels (with respect to the wound image sizes of $240 \times 240 = 57600$ pixels) that were genuinely affected by high-intensity glare, and the results were visually reviewed and verified by experienced practitioners as per relevant guidelines and practice of medical image processing[29–32]. Thirdly, image contrast was improved by stretching the intensity range through the application of Histogram Equalization, which was used while carefully avoiding bias towards specific hues associated with the wounds.[33] Finally, noise reduction was performed using a Gaussian blur filter, without compromising the segmentation accuracy.[34] These additional preprocessing steps were again carefully supervised by the clinical experts in our team to eliminate any potential artificial skewing of the wound image data.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

To further analyze and extract relevant features and measurements of the PIs, each image underwent a segmentation process to isolate the wound pixels from the rest of the image. This segmentation process, illustrated in Figure 2 and described in detail in **Appendix A2**, follows a classic approach of using image processing methodologies.

The next step, after segmenting the wound out of the entire image, is to extract meaningful real-world characteristics and measurements of the wounds out of the given images. To extract the real-world ulcer surface area from the image, a wound size in pixels was calculated by summing the number of pixels representing the wound location in a binary mask generated in the wound segmentation algorithm. After obtaining the wound size in pixels, a conversion from image scale (pixels) to real-world scale (centimeters) was performed. By localizing and segmenting the sticker pixels captured in the image, using a similar method as the aforementioned wound segmentation but with thresholding based on green hue values instead of red, the sticker size in pixels was determined. Assuming a round shape for the sticker, the contour detection algorithm was applied using a built-in OpenCV function to pinpoint its location and calculate its size in pixels.[35] With the sticker size in pixels determined, it functioned as the scaling factor for converting between the image scale in pixels and the real-world scale in centimeters. This conversion enabled the calculation of the real-world wound surface area in centimeters, using the following equation:

$$wound\ size_{RW} = sticker\ size_{RW} * \left(wound\ size_{image} / sticker\ size_{image}\right) \qquad \text{Eq. 1}$$

Where $wound\ size_{RW}$ represents the real-world wound size in centimeters, $sticker\ size_{RW}$ represents the real-world sticker size in centimeters, $wound\ size_{image}$ and $sticker\ size_{image}$ are the wound and sticker size in pixels, respectively.

Accuracy evaluations of the wound segmentation algorithm

After obtaining the wound segmentation and the calculation of the real-world wound surface area out of the digital images, it was necessary to authenticate and evaluate the accuracy of the resulting measurements in comparison to the actual wound segmentation and size determined by the nurses. The manual annotations, indicated by blue line markings, were segmented by detecting pixels with high blue HSV values through thresholding. Subsequently, the Canny edge detection algorithm was employed using a built-in OpenCV function.[36] To ensure the closure of any gaps in the edges, a morphological dilation operation was applied with a 5x5 elliptic kernel. The contours of the closed edges were then detected using OpenCV's contour detection method. Finally, morphological erosion with a 5x5 elliptic kernel was utilized to remove noise, resulting in the final wound segmentation based on the blue[1] annotations, defined as the ‘ground-truth’ wound segmentation determined by the healthcare professionals. The ground-truth wound surface area was also calculated from the annotated images to evaluate the accuracy of the automatic wound surface area calculation, as generated by the suggested method. The ground-truth value of the wound surface area was calculated using Eq. 1, using the sticker segmentation as the scaling reference.

The evaluation of the proposed segmentation method involved comparing the segmentation generated by the suggested method with the ground-truth segmentation. To assess the similarity between the two, the Intersection over Union (IoU) score was employed. The IoU score is a widely used metric for evaluating segmentation tasks,[37] and it was calculated using the following equation:

$$IoU = \frac{|A \cap B|}{|A \cup B|} \qquad \text{Eq. 2}$$

where $A \cap B$ is the intersecting area of the shapes A and B, and $|A \cup B|$ is the area of the union of the shapes A and B.

The generated segmentation was also evaluated by calculating the percentage of intersection of it with the ground-truth wound segmentation to measure the degree of overlap between the two segmentations and to examine the ability of the suggested method to correctly detect the wound location in the entire image.

Results

Patient characteristics and the wound image database

A total of 45 patients were recruited for this research, where 35 of them were females. The patients were aged between 67-98 years and stages 1-3 (including erythema for stage 1), suspected deep tissue injury and unstageable PIs were in the dataset. Skin tone varied between Fitzpatrick Scale 1-5 and the PIs were in three main anatomical areas – bottoms (n=24), heels/ankles (n=15) and toes (n=6).

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

In total, 221 PI images were received for use in the study. The number of images per patient ranged from 1 to 13 (average 4.8). Certain images were excluded from the database due to their poor quality, expressed by blurring, poor image contrast and brightness, bad imaging angle or distance from the target, as well as images in which the green sticker was not captured. In total, 214 images were included in the analysis.

Image processing and data analysis

An example of wound segmentation based on the reported method, as applied on an image of a 98-year-old female patient with PI in the sacrum area, is presented in **Figure 3**. The original image underwent preprocessing to scale the image size, remove glare and noise and to improve image contrast. Then the hue values of the preprocessed image were extracted after converting the RGB image to HSV scale. The thresholding process resulted in a binary mask, where pixels with hue values within the desired range obtain the value of 1, otherwise 0. Subsequently, the resulting binary mask underwent noise reduction and once the final mask was obtained, it was multiplied with the preprocessed image to create a focused segmentation of the wound out of the entire image.

Accuracy evaluations of the wound segmentation algorithm

The blue annotations were successfully detected and segmented out from the entire annotated images based on the method mentioned in section 2.3 and were further determined as the ground-truth wound segmentations. **Figure 4** showcases both the manual wound annotations, indicated by blue markings, and the corresponding successful segmentations derived from these annotations for three different patients with PIs in the sacrum area.

A comparison between the ground-truth wound segmentation and the generated segmentation based on the proposed methodology is illustrated in **Figure 5**. The ground-truth segmentation is presented alongside the generated segmentation over time of a 98-year-old with a stage 2 PI in the sacral area, as of the first documentation of the PI (baseline) and 0-3 weeks afterwards. The IOU score and the intersection percentage of the corresponding segmentations are displayed above each comparison at each time point. In addition, the blue and gray bars represent the wound size in real-world scale (centimeters) as calculated from the ground-truth and the generated wound segmentations respectively.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

The proposed segmentation method accurately identified the wound location in all but one of the annotated images (21 of 22). The one failure occurred where the acquisition process did not adhere to the provided guideline. In this instance, the background of the image was not blank and another object in the background was mistakenly detected as a wound.

The minimum, maximum and average values of the intersection percentages and the IoU scores between the generated and the ground-truth segmentations are presented in Table 1.

Table 1 - Minimum, maximum and average values of the intersections in percentages and the IoU scores calculated based on the ground-truth and the generated segmentations (21 images)

	Minimum	Maximum	Average
Intersection	61.9%	100%	93.9%
IoU score	0.01	0.85	0.34

The high intersection percentages demonstrate that the proposed segmentation succeeded in accurately identifying and segmenting the wound in the images. The calculated IoU scores between the generated and annotated segmentations varied across a wide range of 0.01 to 0.85, where lower scores were observed for very small wounds, while higher scores were obtained for larger wounds. This trend can be attributed to the relative nature of the IoU score. As the size of the wound decreases, any discrepancy or error has a relatively larger impact. For example, an error of 20 pixels in a 50-pixel wound corresponds to a 40% error in terms of percentage, but the absolute error size remains small in relation to the real-world scale.

Discussion

We employed image processing techniques and created an innovative and robust algorithm for segmenting PIs from digital images captured by nurses in clinical practice and extracting the wound surface area in real-world scale. The HSV color space was utilized to analyze the red color values within the image, allowing for the unsupervised detection and segmentation of the wound region from the entire image. To assess the accuracy of the generated wound segmentation, a comparison was made against the ground-truth segmentation.

The proposed methodology, as depicted in **Figure 3**, effectively identifies the wound location in the entire image using established image processing techniques based on HSV color space. By adopting a classic approach to image processing methodologies, the algorithm has the potential to be implemented in healthcare facilities without the need for complex systems or, we believe, extensive staff training. This may ensure the practicality and usability of the methodology in real-world conditions during the health care providers' day-to-day work.

Furthermore, as illustrated in **Figure 5** and detailed in **Table 1**, the algorithm-generated wound segmentation exhibits significant intersection percentages with the ground-truth segmentation. This result highlights the algorithm's accuracy in correctly identifying the wound location within the image, further underscoring the potential for the usefulness of this approach in clinical settings. The development of the current algorithm based on real-world images collected by nurses in a healthcare facility reinforces the potential value of it in real-life scenarios, in contrast to previously published methods which utilized images collected by the research group and/or under controlled laboratory conditions.[38–47]

In addition, the suggested methodology incorporates the surrounding area of the PIs in the segmented wound region which led to a big union area reducing the IoU score. This inclusion aligns with the significance placed on analyzing the surrounding area in the context of wound treatment decision-making as outlined in the Guidelines for the Treatment of Diabetic Ulcers.[8] By segmenting not only the actual wound but also the surrounding area, valuable insights can be gained to help inform treatment decisions. This comprehensive segmentation approach has the potential to contribute meaningfully to the future treatment strategies employed for the wound and for the vulnerable area around it.

According to the Guidelines for the Treatment of Diabetic Ulcers [8] and Pressure Ulcers,[10] wound surface area change is a good indicator for the effectiveness of the current treatment and the healing potential of the wound. Presently, healthcare providers may rely on manual measurements, an approach which is prone to errors due to measurement inaccuracies and deceiving assumptions about irregular wound shapes and sizes. By introducing an automated method for wound size calculations based on digital images captured by healthcare providers during their daily routine and as previously demonstrated by the published work of Yang and colleagues,[48] the accuracy of wound measurements can be substantially improved. The proposed method has demonstrated satisfactory accuracy scores in calculating wound surface area, demonstrated in **Figure 5**. Once the proposed method is shown to be feasible and accurate in a larger study with a larger image dataset, the method may be a valuable tool for wound measurement.

Previously, Yang and colleagues proposed a wound surface area calculation technique based on digital photography and assessed its error rate in comparison to the conventional manual measurement using a tape.[48] The Yang et al. segmentation method, along with other reported approaches published in the literature,[47–50] employed the snake algorithm,[51] which necessitates an initial rough marking of wound boundaries before its application in order to obtain the most accurate wound segmentation in the images. These studies, along with numerous other segmentation strategies detailed in the literature,[19,50] predominantly utilize supervised or semi-supervised machine learning AI models (e.g., neural networks) and image processing techniques that require preliminary wound annotation to attain satisfactory accuracy. In contrast, our current innovative method for wound segmentation, based on the hue values of the image, stands out for its *annotation-free operation*. This direct segmentation approach obviates the necessity for implementing large, memory-intensive pre-trained models that demand intricate code files, thereby enhancing its applicability in clinical settings.

Limitations

The research was constrained by a small image dataset, which may have limited the generalizability of the algorithm's performance. A larger and more diverse dataset would have provided a broader range of wound characteristics and improved the algorithm's robustness. The high variance in image quality posed a challenge to accurately analyze and process the images. The quality of the images (including factors such as lighting conditions, resolution, and focus) significantly influenced the algorithm's performance. In certain cases, inconsistencies in image quality introduced inaccurate detection and segmentation results by the suggested algorithm. Consequently, to mitigate the impact of poor-quality images, a decision was made to exclude them from the dataset, which further reduced the size of the dataset and limited the overall sample size available for analysis. It is important to note that the exclusion of poor-quality images was necessary to maintain the reliability and integrity of the dataset, but it also introduced a potential source of bias and reduced the dataset's representativeness.

Conclusions

Implications for practice

The proposed methodology for wound segmentation (utilizing digital images captured by healthcare providers in clinical settings) represents an innovative approach due to its potential feasibility and applicability in real-life scenarios. As the use of digital imaging for wound documentation purposes becomes increasingly mainstream, implementation of a fully automated methodology for calculating a wound surface area and/or extracting any other relevant features from the acquired digital images holds the potential to support decision-making processes concerning future treatment and the healing potential of the wound.

Recommendations for future research

Further research should address the constraints associated with the small image dataset and the high variance in image quality. A larger and more diverse dataset would enable the algorithm to learn from a broader range of wound characteristics, enhancing its applicability in clinical practice. Furthermore, given that it is not feasible to exert control over the image quality captured by healthcare providers, it is imperative to focus on improving the suggested method by means of extracting meaningful wound characteristics even when the image quality is suboptimal. This will require improving the algorithm's robustness to accommodate a wide range of imaging conditions. By enhancing the algorithm's adaptability and performance under challenging imaging conditions, a more reliable and practical tool can be developed for accurate wound assessment under clinical settings.

We believe that, in the near future, the suggested computerized method for automatic extraction of wound features can be implemented for telehealth purposes, utilizing smartphones and tablets for data collection and connectivity. In such approaches, the computerized algorithm provides immediate automated advice to the local healthcare professional, while the medical information of the patient can also be transferred via cloud computing to a remote human expert who can further guide the local clinician. In this way, the system acts as a supportive tool, complementing the clinical judgments of both the local healthcare professional and the remote clinician.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

References

1. Gefen A, Brienza D, Edsberg L. Prevention and Treatment of Pressure Ulcers/Injuries: Clinical Practice Guideline. European Pressure Ulcer Advisory Panel, National Pressure Injury Advisory Panel and Pan Pacific Pressure Injury Alliance; 2019.

2. Izadi K, Ganchi P. Chronic Wounds. Clinics in Plastic Surgery 2005;32(2):209–222; doi: 10.1016/J.CPS.2004.11.011.

3. Gefen A. How medical engineering has changed our understanding of chronic wounds and future prospects. Medical Engineering & Physics 2019;72:13–18; doi: 10.1016/J.MEDENGPHY.2019.08.010.

4. Nussbaum SR, Carter MJ, Fife CE, et al. An Economic Evaluation of the Impact, Cost, and Medicare Policy Implications of Chronic Nonhealing Wounds. Value in Health 2018;21:27–32; doi: 10.1016/j.jval.2017.07.007.

5. Mission Regional Medical Center. Chronic Wounds: A Growing Problem. n.d. Available from: https://missionrmc.org/services/the-wound-healing-center/chronic-wounds-a-growing-problem/ [Last accessed: 6/1/2023].

6. Järbrink K, Ni G, Sönnergren H, et al. The Humanistic and Economic Burden of Chronic Wounds: A Protocol for a Systematic Review. Systematic Reviews 2017;6(1):1–7; doi: 10.1186/S13643-016-0400-8/PEER-REVIEW.

7. Gefen A. The future of pressure ulcer prevention is here: Detecting and targeting inflammation early. EWMA Journal 2018;19(2):7–13.

8. Steed DL, Attinger C, Colaizzi T, et al. Guidelines for the treatment of diabetic ulcers. Wound Repair and Regeneration 2006;14(6):680–692; doi: 10.1111/J.1524-475X.2006.00176.X.

9. U.S. Department of Health and Human Services Food and Drug Administration. Guidance for Industry: Chronic Cutaneous Ulcer and Burn Wounds - Developing Products for Treatment: Draft - Not for Implementation. 2006. Available from: http://www.fda.gov/cdrh/ggpmain.html [Last accessed: 6/21/2023].

10. Whitney J, Phillips L, Aslam R, et al. Guidelines for the treatment of pressure ulcers. Wound Repair and Regeneration 2006;14(6):663–679; doi: 10.1111/J.1524-475X.2006.00175.X.

11. Sheehan P, Jones P, Caselli A, et al. Percent Change in Wound Area of Diabetic Foot Ulcers Over a 4-Week Period Is a Robust Predictor of Complete Healing in a 12-Week Prospective Trial. Diabetes Care 2003;26(6):1879–1882; doi: 10.2337/DIACARE.26.6.1879.

12. Robson MC, Hill DP, Woodske ME, et al. Wound healing trajectories as predictors of effectiveness of therapeutic agents. Archives of surgery (Chicago, Ill : 1960) 2000;135(7):773–777; doi: 10.1001/ARCHSURG.135.7.773.

13. Anonymous. International Wound Infection Institute - Slough: Composition, Analysis and Effect on Healing. n.d. Available from: https://www.linkforwoundhealing.info/en/scientific-

content/2023/international-wound-infection-institute-slough-composition [Last accessed: 4/5/2024].

14. Keast DH, Bowering ; C Keith, Evans ; A Wayne, et al. MEASURE: A proposed assessment framework for developing best practice recommendations for wound assessment. Wound Repair and Regeneration 2008;12(s1):s1–s17; doi: 10.1111/J.1067-1927.2004.0123S1.X.

15. Papazoglou ES, Zubkov L, Mao X, et al. Image analysis of chronic wounds for determining the surface area. Wound Repair and Regeneration 2010;18(4):349–358; doi: 10.1111/J.1524-475X.2010.00594.X.

16. Foltynski P, Ciechanowska A, Ladyzynski P. Wound surface area measurement methods. Biocybernetics and Biomedical Engineering 2021;41(4):1454–1465; doi: 10.1016/J.BBE.2021.04.011.

17. Foltynski P, Ladyzynski P, Sabalinska S, et al. Accuracy and Precision of Selected Wound Area Measurement Methods in Diabetic Foot Ulceration. https://home.liebertpub.com/dia 2013;15(8):712–721; doi: 10.1089/DIA.2013.0026.

18. Thawer HA, Houghton PE, Woodbury MG, et al. A comparison of computer-assisted and manual wound size measurement. Ostomy/wound management 2002;48(10):46–53.

19. Dabas M, Schwartz D, Beeckman D, et al. Application of Artificial Intelligence Methodologies to Chronic Wound Care and Management: A Scoping Review. Advances in Wound Care 2023;12(4):205–240; doi: 10.1089/wound.2021.0144.

20. Zhang J, Mihai C, Tüshaus L, et al. Wound Image Quality From a Mobile Health Tool for Home-Based Chronic Wound Management With Real-Time Quality Feedback: Randomized Feasibility Study. JMIR Mhealth Uhealth 2021;9(7):e26149 https://mhealth.jmir.org/2021/7/e26149 2021;9(7):e26149; doi: 10.2196/26149.

21. Flanagan M. Improving accuracy of wound measurement in clinical practice. Ostomy/wound management 2003;49(10):28–40.

22. Yin J, Ngiam KY, Teo HH. Role of Artificial Intelligence Applications in Real-Life Clinical Practice: Systematic Review. J Med Internet Res 2021;23(4):e25759 https://www.jmir.org/2021/4/e25759 2021;23(4):1–17; doi: 10.2196/25759.

23. Ronquillo CE, Peltonen LM, Pruinelli L, et al. Artificial intelligence in nursing: Priorities and opportunities from an international invitational think-tank of the Nursing and Artificial Intelligence Leadership Collaborative. Journal of Advanced Nursing 2021;77(9):3707–3717; doi: 10.1111/JAN.14855.

24. Wounds Australia. Standards for Wound Prevention and Management. Australian Medical Association: Osborne Park WA: Cambridge Media; 2023.

25. Miller C, Karimi L, Donohue L, et al. Interrater and Intrarater Reliability of Silhouette Wound Imaging Device. Advances in Skin & Wound Care 2012;25(11):513–518; doi: 10.1097/01.ASW.0000422626.25031.b8.

26. Anonymous. Fitzpatrick skin phototype Genetic (physical traits). n.d.

27. Wu J-M, Tsai C-J, Ho T-W, et al. A Unified Framework for Automatic Detection of Wound Infection with Artificial Intelligence. Applied Sciences 2020, Vol 10, Page 5353 2020;10(15):5353; doi: 10.3390/APP10155353.

28. Anonymous. OpenCV: Image Inpainting. n.d. Available from: https://docs.opencv.org/3.4/df/d3d/tutorial_py_inpainting.html [Last accessed: 5/17/2023].

29. Abel E, Xi W, White P. Methods for removing glare in digital endoscope images. Surg Endosc 2011;25(12):3898–3905; doi: 10.1007/s00464-011-1817-8.

30. Abel EW, Zhuo Y, Ross PD, et al. Automatic glare removal in endoscopic imaging. Surg Endosc 2014;28(2):584–591; doi: 10.1007/s00464-013-3209-8.

31. Nie C, Xu C, Li Z, et al. Specular Reflections Detection and Removal for Endoscopic Images Based on Brightness Classification. Sensors 2023;23(2):974; doi: 10.3390/s23020974.

32. Anonymous. Guidelines for Diagnostic Medical Imaging: ACR–AAPM–SIIM Technical Standard for Electronic Practice of Medical Imaging. 2022.

33. Anonymous. OpenCV: Histogram Equalization. n.d. Available from: https://docs.opencv.org/3.4/d4/d1b/tutorial_histogram_equalization.html [Last accessed: 5/17/2023].

34. Anonymous. OpenCV: Smoothing Images. n.d. Available from: https://docs.opencv.org/4.x/d4/d13/tutorial_py_filtering.html [Last accessed: 5/17/2023].

35. Anonymous. OpenCV: Contours : Getting Started. n.d. Available from: https://docs.opencv.org/4.x/d4/d73/tutorial_py_contours_begin.html [Last accessed: 5/17/2023].

36. Anonymous. OpenCV: Canny Edge Detection. n.d. Available from: https://docs.opencv.org/3.4/da/d22/tutorial_py_canny.html [Last accessed: 5/22/2023].

37. Vineeth S Subramanyam. IOU (Intersection over Union). 2021. Available from: https://medium.com/analytics-vidhya/iou-intersection-over-union-705a39e7acef [Last accessed: 5/18/2023].

38. Song B, Sacan A. Automated Wound Identification System Based on Image Segmentation and Artificial Neural Networks. 2012 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) IEEE: Sch. of Bio Med. Eng., Drexel Univ., Philadelphia, PA, United States BT - 2012 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 4-7 Oct. 2012; 2012; p. 4 pp.; doi: 10.1109/BIBM.2012.6392633.

39. Veredas F, Mesa H, Morente L. Binary tissue classification on wound images with neural networks and bayesian classifiers. IEEE Transactions on Medical Imaging 2010;29(2):410–427; doi: 10.1109/TMI.2009.2033595.

40. Wang L, Pedersen PC, Agu E, et al. Area Determination of Diabetic Foot Ulcer Images Using a Cascaded Two-Stage SVM-Based Classification. IEEE Transactions on Biomedical Engineering 2017;64(9):2098–2109; doi: 10.1109/TBME.2016.2632522.

41. Wang L, Pedersen PC, Agu E, et al. Boundary determination of foot ulcer images by applying the associative hierarchical random field framework. Journal of Medical Imaging 2019;6(2); doi: 10.1117/1.JMI.6.2.024002.

42. Alzubaidi L, Fadhel MA, Oleiwi SR, et al. DFU_QUTNet: diabetic foot ulcer classification using novel deep convolutional neural network. Multimedia Tools and Applications 2019 79:21 2019;79(21):15655–15677; doi: 10.1007/s11042-019-07820-w.

43. Goyal M, Reeves ND, Davison AK, et al. DFUNet: Convolutional Neural Networks for Diabetic Foot Ulcer Classification. IEEE Transactions on Emerging Topics in Computational Intelligence 2018;4(5):728–739; doi: 10.1109/TETCI.2018.2866254.

44. Cui C, Thurnhofer-Hemsi K, Soroushmehr R, et al. Diabetic Wound Segmentation using Convolutional Neural Networks. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS 2019;1002–1005; doi: 10.1109/EMBC.2019.8856665.

45. Goyal M, Reeves ND, Rajbhandari S, et al. Fully convolutional networks for diabetic foot ulcer segmentation. 2017 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2017 2017;2017-Janua:618–623; doi: 10.1109/SMC.2017.8122675.

46. Wang C, Anisuzzaman DM, Williamson V, et al. Fully automatic wound segmentation with deep convolutional neural networks. Scientific Reports 2020 10:1 2020;10(1):1–9; doi: 10.1038/s41598-020-78799-w.

47. Loizou CP, Kasparis T, Mitsi O, et al. Evaluation of wound healing process based on texture analysis. IEEE 12th International Conference on BioInformatics and BioEngineering, BIBE 2012 2012;709–714; doi: 10.1109/BIBE.2012.6399754.

48. Yang S, Park J, Lee H, et al. Error rate of automated calculation for wound surface area using a digital photography. Skin Research and Technology 2018;24(1):117–122; doi: https://doi.org/10.1111/srt.12398.

49. Ferreira F, Pires IM, Costa M, et al. A Systematic Investigation of Models for Color Image Processing in Wound Size Estimation. Computers 2021;10(4); doi: 10.3390/computers10040043.

50. Zahia S, Garcia Zapirain MB, Sevillano X, et al. Pressure injury image analysis with machine learning techniques: A systematic review on previous and possible future methods. Artificial Intelligence in Medicine 2020;102; doi: 10.1016/j.artmed.2019.101742.

51. Xu C, Prince JL. Gradient Vector Flow: A New External Force for Snakes. In: Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition 1997; pp. 66–71; doi: 10.1109/CVPR.1997.609299.

52. Rose-McGuckin K. IMI National Guidelines. A Guide to Good Practice. Wound Management Photography. 2022.

53. Jacob K. Best practice for capturing and presenting accurate wound images. Wounds UK 2019;15(1):58–61.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

54. Sperring B, Baker R. Ten top tips for taking high-quality digital images of wounds. Wounds International 2014;9(2):62–64.

55. Gefen A, Brienza D, Edsberg L, et al. The Etiology of Pressure Injuries. In: Prevention and Treatment of Pressure Ulcers/Injuries: Clinical Practice Guideline European Pressure Ulcer Advisory Panel (EPUAP), National Pressure Injury Advisory Panel (NPIAP) and the Pan Pacific Pressure Injury Al. 2019.

56. Carper WJ, Lillesand TM, Kiefer RW. The Use of Intensity-Hue-Saturation Transformations for Merging SPOT Panchromatic and ~ultispectral Image Data. In: PHOTOCRAMMETRIC ENGINEERING AND REMOTE SENSIN Madison; 1990; pp. 459–467.

57. OpenCV: Changing Colorspaces. n.d. Available from: https://docs.opencv.org/4.x/df/d9d/tutorial_py_colorspaces.html [Last accessed: 5/22/2023].

58. Image Analysis - Connected Components Labeling. n.d. Available from: https://homepages.inf.ed.ac.uk/rbf/HIPR2/label.htm [Last accessed: 5/17/2023].

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

Appendix A1

Image acquisition protocol

The process below applies to the collection of the PU/PI images in this project. The process has been informed by published recommendations for wound imaging[52–54].

A1.1 Preparation

1. Access a facility owned and operated smartphone, tablet or digital camera and a clean green dot sticker.
2. Position the participant so that comfort and safety are assured, lighting is optimal, and so that you can easily take the image at a perpendicular angle to the PU/PI.
3. Write the study Participant ID number and date on the green dot sticker.
4. Place the green dot sticker near the PU/PI.
5. Check that identifiable features of the participant, other people and items in the environment will not be included in the image of the PU/PI.
6. Check that the flash of the smartphone or tablet camera is enabled. If using a digital camera, select the auto-focus setting unless you are confident focussing the camera manually.

A1.2 Acquisition of the wound images

7. Hold the smartphone, tablet or digital camera perpendicular to the PU/PI so that the entire PU/PI and green dot sticker are visible in the image frame.
8. If using a smartphone or tablet, use the “tap screen to focus” (or similar) option to ensure that the PU/PI is clear in the screen view.
9. Check (again) that the image is clear, that the PU/PI is in focus, that the green sticker is fully visible, and that the entire wound is visible.
10. Take the image (and re-take the image, if necessary, to obtain the best quality image).
11. Remove the green dot sticker and clean the associated skin area.
12. Redress the PU/PI as per the care plan.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

Appendix A2

Detailed description of the wound segmentation

Since redness is a common characteristic of PIs caused by continuous mechanical loading/movement on the skin[2],[55] the presence of red color in an image can serve as a strong indicator of pixels describing the wound location in the image. An effective way of identifying red color in an image is by analyzing its hue values, representing the relative proportion of red, green and blue inputs in a digital image.[56] In order to extract the hue values, the image was converted from Red-Green-Blue (RGB) color space to Hue-Saturation-Value (HSV) color space using OpenCV Python library.[57] After extracting the hue values from the HSV image, a thresholding process was applied to identify pixels with high red values. The thresholding method created a binary mask, where pixels within the defined range obtained the value of 1, and all other pixels obtained the value of 0. Subsequently, noise was removed from the generated mask by applying morphological opening and closing [33] with a 3×3 elliptic kernel, eliminating noise pixels by converting their values from 1 to 0. The remaining pixels in the mask with the value of 1 after noise removal were considered as suspected wound pixels. Those pixels were then grouped and classified by utilizing a "connected components" algorithm, a labeling technique which groups an image’s pixels into components based on their values and neighborhood relationship.[58] Morphological closing with a large 30x30 elliptic kernel was then applied to eliminate all irrelevant groups from the resulting mask and to keep only the largest pixel group. The resulting mask was finally identified as the wound location in the image, in which pixels representing wound location are assigned a value of 1, while the remaining pixels are assigned a value of 0. To obtain the wound segmentation, the preprocessed image was multiplied by the binary mask, resulting in a focused segmentation of the wound out of the entire image.

[2] Generally, redness may also be associated with rash or inflammation unrelated to a PU, hence clinical judgement is still needed for a differential diagnosis.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

Figure captions

Figure 1	The process of acquisition of digital wound photographs outlined in the current protocol. As depicted here, the protocol specified a distance of the phone camera, posture and angle at which the camera should be positioned in relation to a sacral wound.
Figure 2	Pipeline of the suggested wound segmentation algorithm, based on advanced image processing methodologies. The algorithm was applied on image database collected by the nursing staff under clinical setting conditions. RGB – red-green-blue image color space; HSV= hue-saturation-value image color space.
Figure 3	Wound segmentation algorithm results as applied on an image of a 98-year-old female patient with a pressure injury (PI) in the sacrum area. (a) Original image as captured by the nursing staff; (b) preprocessed image after size scaling, glare and noise removal and contrast enhancement; (c) hue values extraction; (d) thresholding using red hue values; (e) final wound segmentation after applying the resulting mask on the preprocessed image.
Figure 4	Annotated images (left column) indicating the location of the wound as provided by the healthcare professionals (marked in blue), and the corresponding wound segmentations (right column) based on the given annotations. Patient 13 is an 80-year-old female patient with unstageable pressure injury (PI) in the gluteal fold; patient 18 is an 81-year-old female with an SDTI in the right buttock; patient 87 is a 98-year-old female patient with a stage 2 PI in the sacrum area. The resulting wound segmentations are defined hereafter as the 'ground-truth' wound segmentations.
Figure 5	Comparison between the ground-truth and the generated wound segmentations over time of a 98-year-old female patient with a pressure injury (PI) in the sacrum area. The baseline indicates the initial documentation of the injury by the nursing staff, while the subsequent time points represent the number of weeks that have passed since the first documentation of the injury. Intersection over Union (IoU) score is indicated above each comparison along with the percentage of intersection measuring the degree of overlap between the two segmentations. Blue and gray bars demonstrate the wound size in cm^2 as extracted from the ground-truth and the generated segmentations, respectively.

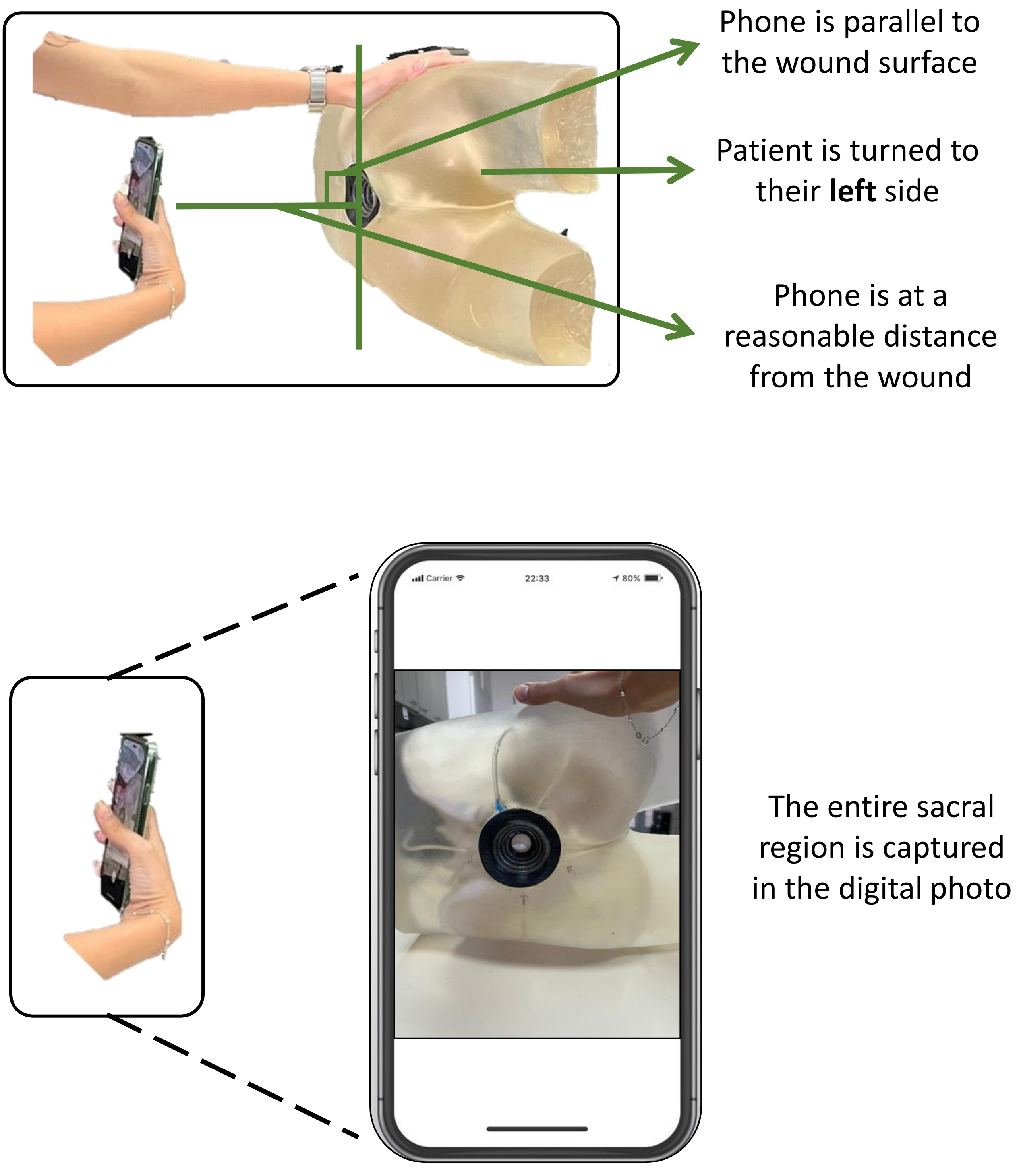

Figure 1

Dabas M, Kapp S, Gefen A. Utilizing Image Processing Techniques for Wound Management and Evaluation in Clinical Practice: Establishing the Feasibility of Implementing Artificial Intelligence in Routine Wound Care. Adv Skin Wound Care. 2025 Jan-Feb 01;38(1):31-39. doi: 10.1097/ASW.0000000000000246.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

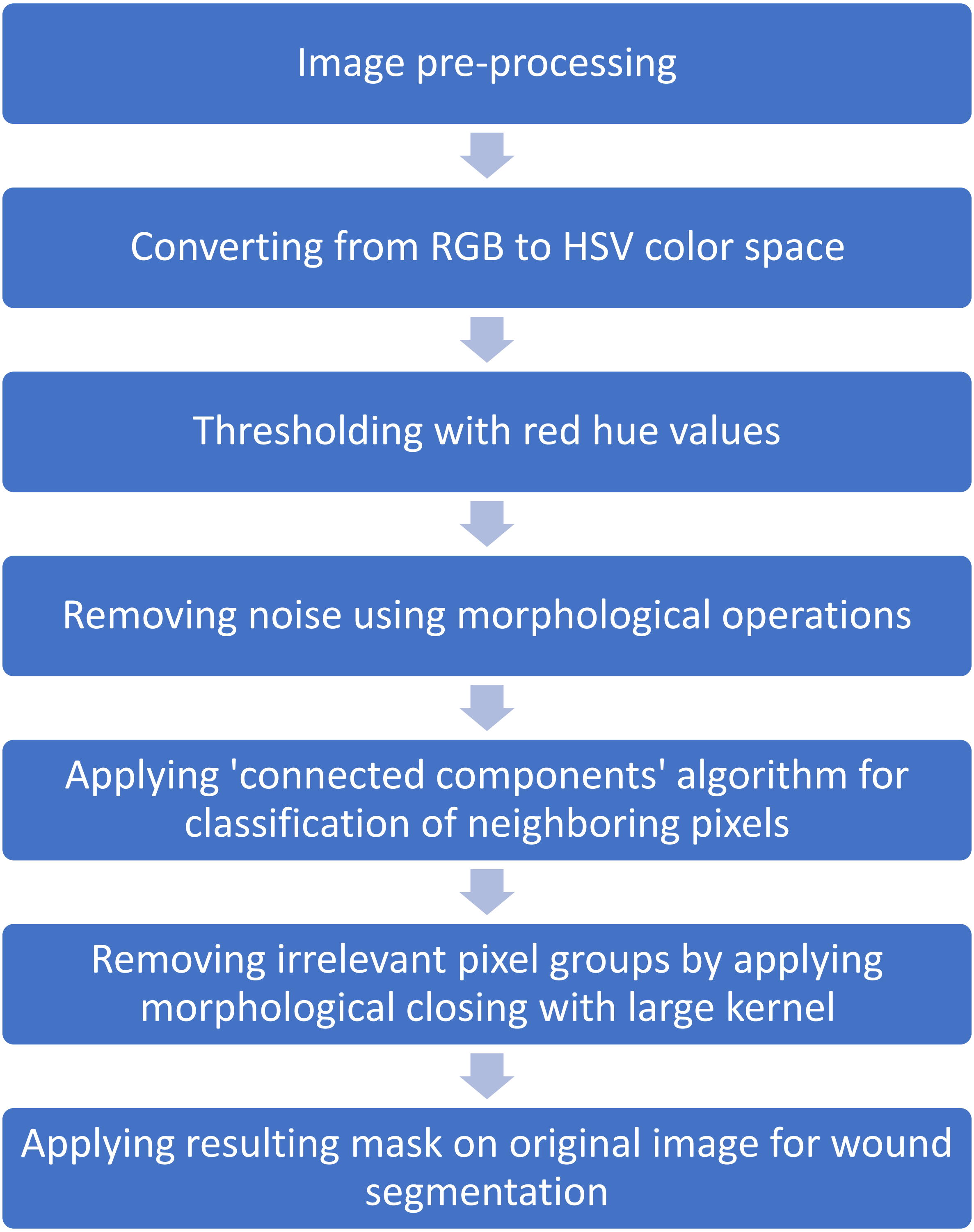

Figure 2

Dabas M, Kapp S, Gefen A. Utilizing Image Processing Techniques for Wound Management and Evaluation in Clinical Practice: Establishing the Feasibility of Implementing Artificial Intelligence in Routine Wound Care. Adv Skin Wound Care. 2025 Jan-Feb 01;38(1):31-39. doi: 10.1097/ASW.0000000000000246.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

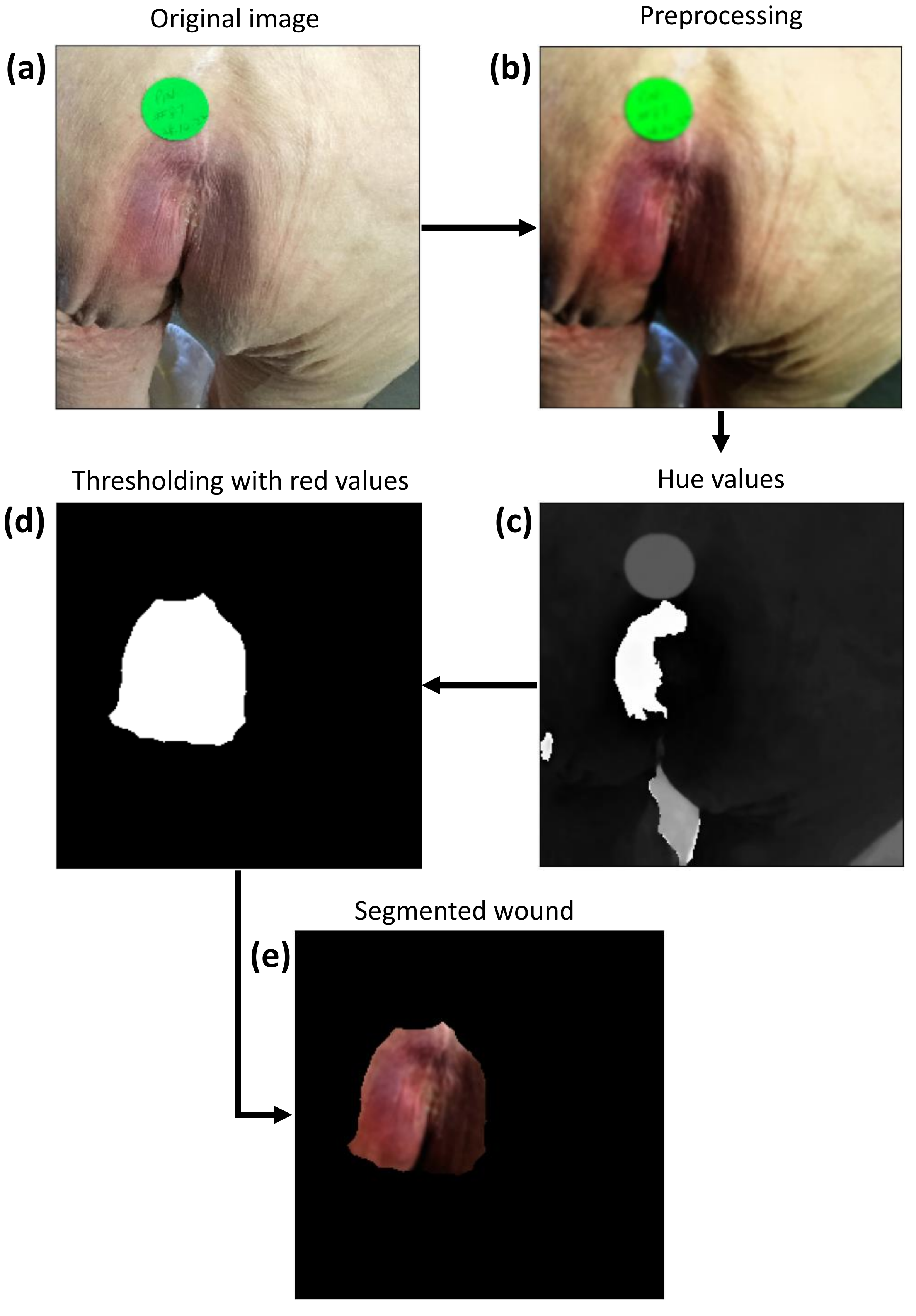

Figure 3

Dabas M, Kapp S, Gefen A. Utilizing Image Processing Techniques for Wound Management and Evaluation in Clinical Practice: Establishing the Feasibility of Implementing Artificial Intelligence in Routine Wound Care. Adv Skin Wound Care. 2025 Jan-Feb 01;38(1):31-39. doi: 10.1097/ASW.0000000000000246.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

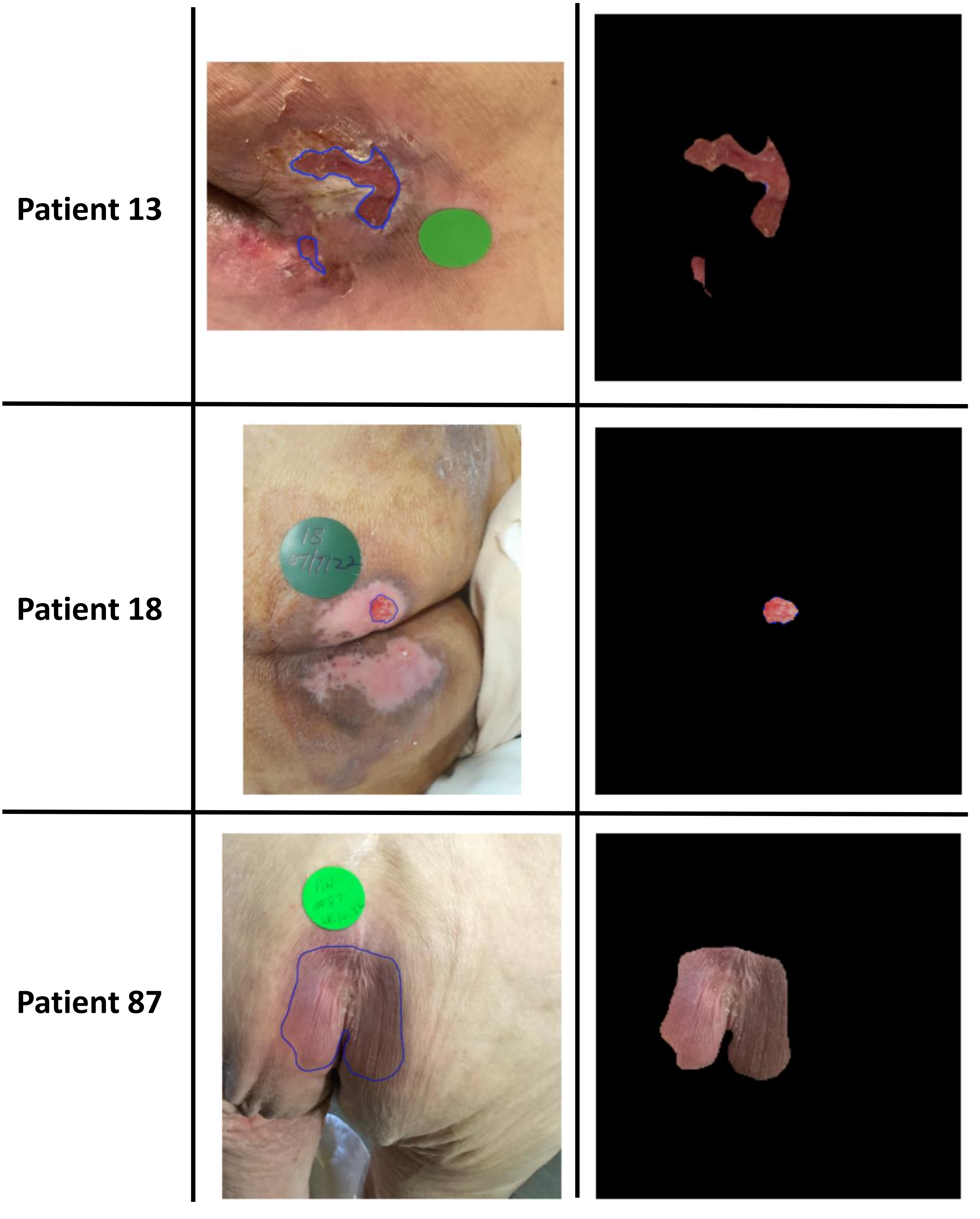

Figure 4

Dabas M, Kapp S, Gefen A. Utilizing Image Processing Techniques for Wound Management and Evaluation in Clinical Practice: Establishing the Feasibility of Implementing Artificial Intelligence in Routine Wound Care. Adv Skin Wound Care. 2025 Jan-Feb 01;38(1):31-39. doi: 10.1097/ASW.0000000000000246.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.

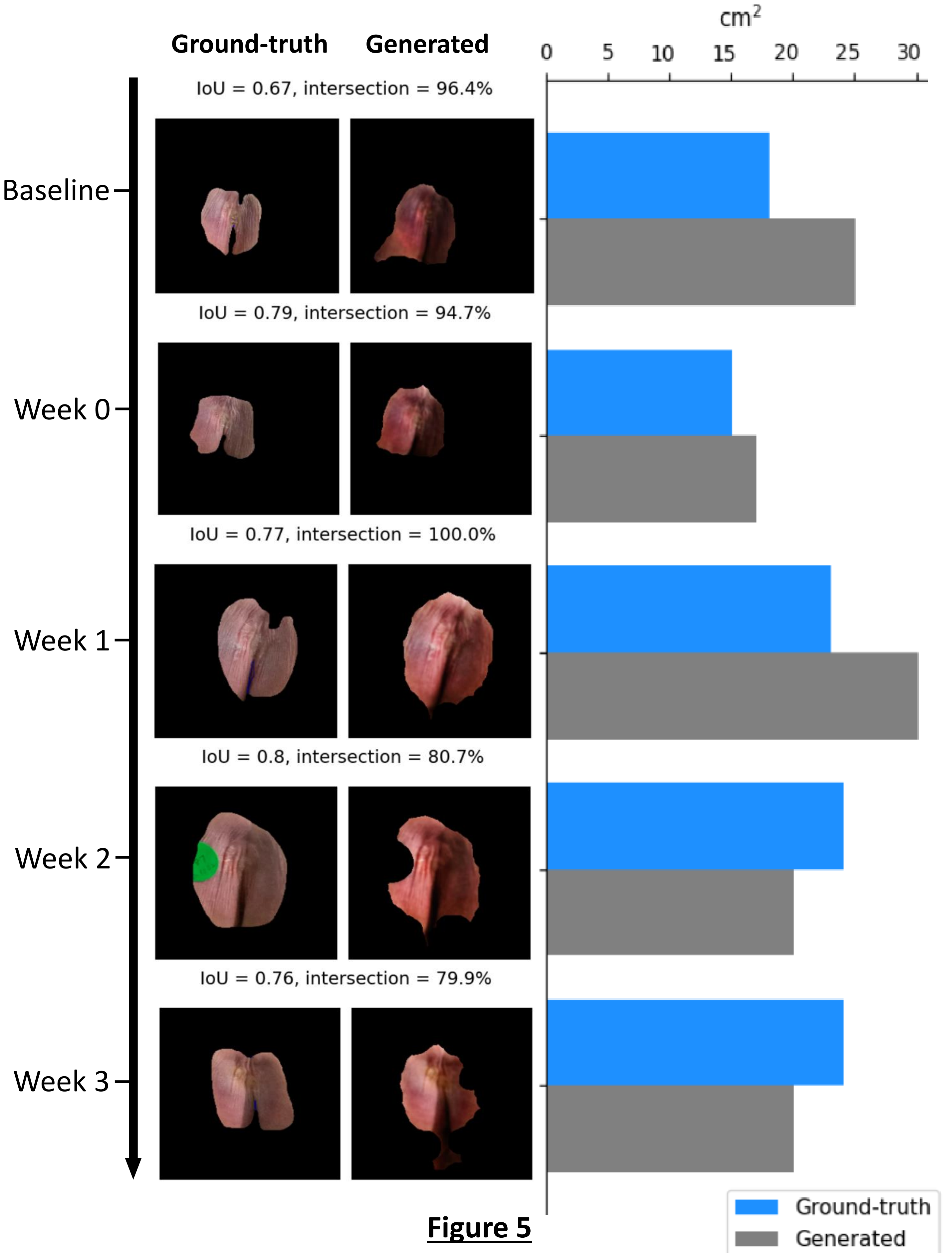

Figure 5

Dabas M, Kapp S, Gefen A. Utilizing Image Processing Techniques for Wound Management and Evaluation in Clinical Practice: Establishing the Feasibility of Implementing Artificial Intelligence in Routine Wound Care. Adv Skin Wound Care. 2025 Jan-Feb 01;38(1):31-39. doi: 10.1097/ASW.0000000000000246.

Provided to the Hasselt University Library Officer for their repository, in accordance with the Belgian Open Access legislation.