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Review

# Artificial Intelligence in Wound Care: A Narrative Review of the Currently Available Mobile Apps for Automatic Ulcer Segmentation

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**Abstract: Introduction:** Chronic ulcers significantly burden healthcare systems, requiring precise measurement and assessment for effective treatment. Traditional methods, such as manual segmentation, are time-consuming and error-prone. This review evaluates the potential of artificial intelligence (AI)--powered mobile apps for automated ulcer segmentation and their application in clinical settings. **Methods:** A comprehensive literature search was conducted across PubMed, CINAHL, Cochrane and Google Scholar databases. The review focused on mobile apps that use fully automatic AI algorithms for wound segmentation. Apps requiring additional hardware or needing more technical documentation were excluded. Vital technological features, clinical validation, and usability were analysed. **Results:** Ten mobile apps were identified, showing varying levels of segmentation accuracy and clinical validation. However, many apps did not publish sufficient information on the segmentation methods or algorithms used, and most lacked details on the databases employed for training their AI models. Additionally, several apps were unavailable in public repositories, limiting their accessibility and independent evaluation. These factors challenge their integration into clinical practice despite promising preliminary results. **Discussion:** AI-powered mobile apps offer significant potential for improving wound care by enhancing diagnostic accuracy and reducing the burden on healthcare professionals. Nonetheless, the lack of transparency regarding segmentation techniques, unpublished databases, and limited availability of many apps in public repositories remain substantial barriers to widespread clinical adoption. **Conclusion:** AI-driven mobile apps for ulcer segmentation could revolutionise chronic wound management. However, overcoming limitations related to transparency, data availability, and accessibility is essential for their successful integration into healthcare systems.

**Keywords:** artificial intelligence; ulcer segmentation; mobile; apps; wound care; deep learning

## 1. Introduction

Chronic ulcers are well recognised as a significant burden in healthcare, significantly affecting patient quality of life and imposing economic strain on health systems[1]. The prevalence of chronic wounds is estimated to be rising, currently at 2.21 cases per 1,000 individuals [2]. Therefore, it is more important than ever to adopt effective strategies that facilitate accurate wound assessment, enable the selection of the most effective evidence-based treatments, and achieve desired patient outcomes[3].

Assessing cutaneous ulcers typically involves measuring their size and observing their composition, making using accurate and reliable measurement tools essential. Traditionally, this

assessment has depended on manual segmentation and measurement, a time-consuming process also prone to human error[4].

Furthermore, the shape and appearance of a wound provide valuable insights into its aetiology, severity, and prognosis; therefore, regularly monitoring these features helps professionals to assess healing progress and select the most appropriate interventions[5]. In addition, numerous studies have demonstrated that photographing a wound facilitates a more comprehensive assessment and reliable monitoring[6,7].

In recent years, artificial intelligence (AI) has emerged as a promising tool in wound care, particularly for segmenting and assessing ulcers[8]. AI-based mobile apps are increasingly being developed to assist physicians and nurses in this area, offering automatic, consistent, and accurate wound assessments. Apps can have one-to-many built-in features, including wound size and depth measurement, localisation and segmentation, tissue classification, manual entry of wound characteristics for documentation and monitoring, and more. Apps are developed from essential colour detection to advanced machine learning algorithms, including convolutional neural networks (CNNs), to provide ulcer analysis and generate accurate segmentation[9]. Such tools can guide clinical decision-making, reduce the burden on healthcare professionals, and improve patient outcomes[10].

Deep learning is currently the most commonly used technique for wound analysis and is one of the most active research areas; indeed, the development of hardware and equipment capable of capturing, classifying, and segmenting images to aid healthcare professionals' diagnostic accuracy appears promising[9]. However, the high heterogeneity of lesion types, image background composition, and acquisition conditions challenge image segmentation[11,12].

The increasing use of AI technologies and handheld devices such as smartphones has led to the timely development of remote diagnostic and prognostic systems for wound care[13]. For example, smartphone cameras have enabled the capture of images and the development of analysis algorithms to assess wound area, segment, and extract colour correlated with wound tissue[14].

The increasing global use of these devices has contributed to the development of numerous applications aimed at skin wound management. These apps allow the collection of chronologically catalogued images that are useful for follow-up[15]. These mobile apps appear to have considerable potential and could be valuable tools for professionals working in the field[16].

This literature review aims to provide an updated overview of mobile applications for wound assessment and automatic segmentation of skin ulcers. Furthermore, the applied technological frameworks and their clinical validation will be scrutinised to investigate their application in real-world clinical settings. Finally, we will discuss the challenges and limitations of these technologies, along with the future directions for research and development in this rapidly evolving field.

## **2. Material and Methods**

### *2.1. Literature Search Strategy*

A literature search was conducted to identify AI-powered mobile applications for automatic wound segmentation and assessment. Databases, including PubMed, Cinhal, Cochrane, Google Scholar, and IEEE Xplore, were searched for peer-reviewed studies published between 2015 and 2024. The keywords used in the search included "ulcer segmentation," "wound care," "mobile apps," "artificial intelligence," and "machine learning." Additionally, the search included app repositories such as Apple App Store and Google Play Store to identify relevant commercial applications. The inclusion criteria for the apps required their declared usability on mobile platforms and the use of automatic AI algorithms for wound segmentation (with no need to provide manual/semi-automatic inputs). Apps that required additional hardware or those without sufficient technical documentation were excluded.

2.2. Data Extraction

For each application, data on the segmentation technique (e.g., edge detection, pixel counting, deep learning), algorithm type, and dataset used for training were extracted. If available, information on the validation method, such as comparing algorithmic segmentation with clinician assessments, was also collected. The presence of public datasets, the algorithm’s transparency (e.g., black-box or explainable AI), and the availability of published results were documented.

2.3. App Selection Criteria and Scoring Classification

We used the following parameters to evaluate the apps:

- Up to 2 points if approved by FDA and/or European agencies.
- Up to 2 points for the availability on mobile platforms (iOS or Android).
- Up to 2 points in case of sufficient peer-reviewed studies or validation data supporting the app’s segmentation capabilities availability.
- Up to 2 points in case of a disclosed method/algorithms and public dataset.
- Up to 10 points based on the mean rates of inter-rater reliability data between AI apps and other assessment and segmentation accuracy metrics such as rule or pencil method, pixel-based accuracy, dice similarity coefficient, and area under the curve (AUC) scores, when available.

3. Results

Ten apps met the inclusion criteria, each with declared performance levels, inconsistent public datasets availability, and clinical validation. The apps’ evaluation also found varying accuracy and reliability in AI-powered ulcer segmentation.

[Table 1] provides a brief description of each app, including its main features and characteristics.

Table 1. Caption.

App name	State	Company, industry, other	Available on app stores and/or public repositories?	Studies	Health care agency evaluation?	Public data set?	Segmentation technique	Reliability	Our classification
Wound at/home healthy.io Minute for Wound	Israel	Healthy.io, a private company	2/2 (App-store, android store)	1/2	2/2, Yes	No	N/A	N/A	5/18
Wound Vision Scout	USA	Wound Vision LLC,	N/a	2/2	No	No	N/A	N/A	2/18

App Mobile		a private company							
APD Skin Monitoring App	Singapore	APD Lab, Private Company	2/2 (App-store, android store)	1/2 Scarves	No	No	1/1 Grabcut[27] , RGB thresholds[28]	N/A	4/18
NdKare app	Singapore	Nucleus Dynamics Pte. Ltd, Private Company	2/2 (App-store, android store, other repositories)	2/2	2/2, Yes	No	1/1 For 2d reconstruction: pixel analysis[50].	10/10[51]	17/18
Clinicram	Spain	Skilled Skin SL, Private Company	No	No	2/2, Yes	No	N/A	N/A	2/18
Swift Skin and Wound	Canada	Swift Medical Inc	No	2/2	2/2, Yes	No	1/1, AutoTissue: tissue segmentation model; AutoTrace: wound segmentation model	10/10[37]	15/18

Care4wounds	Singapore	Tetsuyu Healthcare Holdings Pte Ltd	2/2 (App-store, android store)	2/2	2/2, Yes	No	N/A	9/10[39]	15/18
Tissue Analysis	USA	Net Health Company	2/2 (App-store, android store)	2/2	No	No	N/A	10/10[43]	14/18
ImitoWound	Switzerland	Imito AG	2/2 (App-store, android store)	2/2	No	No	N/A	10/10[52]	14/18
Wound WiseIQ	USA	Med-Compliance IQ, Inc.	No	No	2/2	No	N/A	N/A	2/18

### 3.1. Healthy.io's MinuteFul for Wound (2019, Israel)

MinuteFul for Wound (Also named wound at home app) by Healthy.io, launched around 2019, is an advanced digital tool designed to improve wound care management using AI-powered computer vision and 3D wound imaging.[17] Based in Tel Aviv, Israel, with offices in Boston, USA, and London, UK, the app allows healthcare providers to assess wounds accurately using smartphone cameras and calibration stickers. It standardises wound measurements across various lighting conditions and offers a comprehensive system for tracking wound progression. The app is FDA-registered and CE-marked, ensuring compliance with global medical device standards. However, no detailed data has been published on the specific segmentation techniques employed by the app's camera or the image database used in developing the AI algorithms[17]. The data published on segmentation techniques for Healthy.io's MinuteFul for Wound refer to its use of AI-powered computer vision and 3D wound imaging integrated with smartphone cameras[18,19]. The system employs colour calibration stickers to ensure consistent measurements across lighting conditions. However, these details apply only to the external calibration used during wound assessment and monitoring through the app, not specifically for internal methods like segmentation via camera alone.

Currently, there is no detailed published data regarding the segmentation techniques explicitly employed by the app's camera without additional devices, nor any information on the image database used to develop the segmentation models. The only data published are clinical, regarding its efficacy in providing telemedicine healthcare support [20–22]

### 3.2. Wound Vision Scout App Mobile (USA, 2019)

The WoundVision Scout Mobile app[23], released in 2019, is a comprehensive wound imaging and documentation solution developed by WoundVision LLC. The app integrates an eco-system, principally the use of long-wave infrared thermography (LWIT) using an external device that is FDA



510(k) cleared (K131596) and HIPAA-compliant, designed to streamline wound assessment and integrates seamlessly into electronic medical records (EMRs). However, our exclusive interest is its camera-based wound documentation and assessment capabilities. The hardware instruments, such as the Scout multi-modal imaging device, are beyond the scope of this review. The mobile app analysed provides visual photography using a mobile phone app to record, assess and document wounds, particularly hospital-acquired pressure injuries (HAPIs).

The published data on segmentation techniques[24,25] only apply to the external thermal camera device (like the Scout device used in the studies). The app was claimed to be downloadable and available in stores (like Google Play) but is hardly retrievable in repositories, and there is no published data supporting the segmentation methods employed by the smartphone camera app. Furthermore, there is no information available on the number or source of images used in the app's development or on any associated image database.

### 3.3. APD Skin Monitoring App (Singapore, 2019)

APD Lab, based in Singapore, developed the APD Skin Monitoring App in collaboration with APD SKEG Pte Ltd. It was initially part of a project aimed at improving wound care by using smartphone technology to help patients and healthcare providers monitor wound healing. The app is available on both the Google Play and Apple App Store and was first released in 2019[26].

The APD Skin Monitoring App performs wound segmentation using two main approaches:

1. GrabCut Algorithm: This method uses an interactive segmentation based on graph cuts, requiring the user to draw a rectangle around the wound. While accurate, it is slow and demands manual input, making it less efficient[27].
2. Color Thresholding: The second approach leverages colour detection based on typical wound hues (e.g., shades of red). It quickly separates wound pixels from the background and uses contour detection for area calculation. This method is faster and more accurate[28].

The APD Skin Monitoring App lacks published data regarding its clinical efficiency, database, or formal results comparison. In the development process, the app primarily relied on wound images from a single volunteer for testing, which were used to demonstrate the functionality of its image processing algorithms. While these internal tests showed promising results regarding wound detection accuracy and processing speed, no extensive clinical trials or formal studies have been published to validate its effectiveness in broader patient populations[26].

### 3.4. NDKare App (Singapore, 2019)

The NDKare app was developed by Nucleus Dynamics Pte. Ltd., Singapore and is designed for secure and fast sharing of wound images between patients, clinicians, and healthcare organisations. The app's first data were shared in 2018 [29], and it allowed users to upload realistic wound photos directly from their smartphone, making them accessible from any desktop or mobile device for further review. It also said FDA registration, CE marking, and HSA approval, ensuring that it meets necessary regulatory standards for medical devices.

The app provides a practical tool for wound assessment, making it easier to track wound healing and share data with healthcare providers efficiently. As of its latest update in June 2019, it focuses on improving the user experience and secure handling of sensitive medical data. NDKare is available for download on different app repositories.

In the only known study, the use of a proprietary database of approximately 60 patients with 203 measurements was described for its programming [29]:

- For 2D wound segmentation, the NDKare app uses an image processing technique that automatically distinguishes the wound area from surrounding tissue based on pixel analysis. The app identifies the ulcer boundaries and allows users to adjust the outline if needed manually. This segmentation calculates 2D metrics such as length, width, perimeter, and surface area, offering precise measurements of wounds captured by the smartphone's camera.
- For 3D wound segmentation is based on "structure from motion". This technique creates a 3D model by analysing a video of the wound, capturing images from different angles, identifying

key points, and reconstructing the wound in 3D using triangulation. The app then generates a "dense 3D point cloud" and a smooth surface reconstruction for depth and volume measurement. To date, the site is offline, and the application cannot be downloaded.

### 3.5. Clinic Gram (Barcelona, 2019)

Clinicgram [30] was developed by Skilled Skin SL, a company based in Barcelona, Spain. The app was first released in 2019 as a solution for managing and diagnosing chronic wounds and other clinical conditions using smartphone technology. It is a Class I medical device certified under European standards, specifically ISO 13485:2016.

The producer declared that it uses AI-based algorithms to automatically analyse clinical images and segment various wound parameters. These include detecting the wound's perimeter, area, and tissue types and helping clinicians assess wound progression.

However, neither the database size nor the segmentation technique is disclosed, nor is there data on its efficiency in wound recognition and segmentation.

Furthermore, no articles or scientific works have been published relating to this application, which is reported to be in the course of "clinical trials" and described as a CE class IIb-certified device.

### 3.6. Swift Skin and Wound App (Canada, 2017)

The Swift Skin and Wound App was developed by Swift Medical, Canada[31]. The medical device enables the capture, measurement, and documentation of wound progression and was presented in 2017[32]. The app can work on most iOS and Android devices and complies with HIPAA (Health Insurance Portability and Accountability Act 1996, USA) and PHIPPA (Personal Health Information Protection Act 2004, Canada).

Swift Skin and Wound App use an Artificial Intelligence algorithm to measure wound circumference, type, and progress accurately.

An update of the models used by the digital tool was presented in 2022Comment: To appear in the European Conference on Computer Vision (ECCV), 2014[33]:

- YoloV3[34]: a separate object detection model
- AutoTrace[33]: the segmentation model for lesion localisation is a deep convolutional coding-decoding neural network with attention gates in jump connections.
- AutoTissue[35,36]: the segmentation model for wound tissue is a convolutional encoder-decoder neural network using an EfficientNetB0 architecture as an encoder

Tissue segmentation was considered good/discreet in terms of tissue identification and quality.

These models were trained using 465,187 and 17,000 image-label pairs, respectively, the largest and most diverse chronic wound image dataset in terms of wound types and skin tones.

The measurement is done through the application of a small HealX<sup>TM</sup> reference adhesive marker, applied next to the wound, during image acquisition, acting as a scale and colour reference.

The published data regarding the accuracy are quite good: App ICC for measuring height and width showed a mean ICC of 0.86 [0.75-0.94 range] and has been shown to be 57% faster than the traditional ruler method and charting on paper[37].

Specific published data regarding the segmentation and area calculation in a testing set showed an ICC of 1 (0.99-1), Even if the wounds on which the measurements were performed were of a low number and in a specific environment[32].

Moreover, the app allows interfacing with other devices (such as FLIR One<sup>TM</sup>) to assess wound temperatures.

The Swift Skin and Wound solution includes a dashboard to view a full range of statistics and trends on the patient population; it allows the export of images, measurements, assessments and treatments via PDF documents. All patient data are protected and encrypted. Finally, patients and caregivers for home monitoring can also use the tool.

### 3.7. Cares4wounds (Singapore, 2019)



Cares4wounds (C4W) is a Wound Care Imaging, Assessment and Management System, developed by Tetsuyu Healthcare Holdings Pte Ltd[38]. The purpose of this tool is to provide a standardized approach to monitoring wound healing progress by using an approach non-contact.

The system consists of a software application that is utilised with commercial off-the-shelf (COTS) Apple mobile computing platforms (iPad with 3D structure sensor and iPhone with dual camera) and a web-based software application that is optimised for mobile platforms. The mobile application is supported on iPhone 11 or an equivalent device (no attachment sensor or reference sticker required) or alternatively on any iPad with an attached Structured Sensor. The application is accessible in the Apple App Store. C4W is available in two versions; while the C4W-A is designed only for iPad mini 5th generation with Structure Sensor, the C4W-B is also supported by iPhone 11 or later. The C4W-A version uses a point-and-measure system to measure the length, width and depth of wounds, while the tissue classification is manual. In contrast, the CW4-B version has automatic tissue classification (based on epithelisation, granulation, necrotic, and slough) and measurement. Both versions allow for recording clinical documentation and conducting teleconsultations. The patient's data can be accessed remotely through a secured web portal to improve overall patient management. Additionally, the CAW-B has received the CE mark and is listed in the HSA Class B Medical Device Register for Singapore.

Chan et al. conducted a study to validate the C4W system against traditional wound assessment measurements in 28 patients diagnosed with diabetic foot ulcers. The study evidences optimal inter-rater reliability of C4W measurements for length (range 0.825–0.934), width (range 0.825–0.930), and area (range 0.872–0.932) against traditional wound assessment by a trained specialist wound nurse [39].

Kitamura et al published a case study of a 90-years-old woman presenting with a pressure injury during the COVID-19 pandemic[40]. The visiting nurse utilized the C4W app to conduct teleconsultations with a wound care specialist. By assessing the wound through the C4W app, they asserted how they have been able to provide valuable instructions for patient assistance, leading to better wound care.

Data on the segmentation technique, database size, efficiency in wound recognition are not available; although the data published by Chan et al[39] showed a good inter-rater reliability of C4W measurements of wounds, these was limited to length, width and area (not available on depth and undermining) and to diabetic foot ulcers.

### 3.8. Tissue Analysis (USA, 2014)

The Tissue Analysis (TA) app is a cloud-based application that uses machine learning and computer vision to autonomously segment, classify, and measure wounds and assist in wound treatment[41]. It was developed in 2014 by Tissue Analytics, Inc., and then the start-up was acquired by Net Health Company in 2020. It was developed by Capturing an image of the wound, enabling the TA app to analyse its dimensions, perimeters, surface area, and tissue composition.

The app is available for iOS and Android devices with an integrated camera. There is no need for additional optics or hardware. The TA app includes a clinician interface that allows for taking photos and documenting wound assessment and management, and an interface for patients to monitor wounds that is connected to the clinician interface for oversight.

The Net Health company has released data that shows a measurement error of less than 5% when using the TA app compared to conventional methods.

The TA app was granted Breakthrough Device Status by the FDA in 2022.

Data on the segmentation technique or database size is not available.

The study conducted by Barakat-Johnson et al. aimed to evaluate the usability and effectiveness of the TA app to improve wound assessment and management[42]. Using the TA app for wound care in 124 patients during the COVID pandemic, a significant improvement in wound documentation and remote patient monitoring was demonstrated. The wound management schedule showed a 6.1% improvement when compared to standard care patients, with a 32.8% improvement in pain, 91.7% improvement in size, 55.2% improvement in exudate, and 38.7% improvement in odour. According

to the authors, the app has the ability to capture wound images, integrate EMR, aggregate wound data, integrate telehealth, and provide clinical decision-support capability.

Another study by Fong and colleagues aimed to verify the clinical inter-rater reliability of the TA app in measuring venous leg ulcers by comparing it to traditional wound assessment measurements conducted by a trained wound nurse[43]. The inter-rater reliability between traditional standard measurements and TA measurements ranged from 0.799 to 0.919. The inter-rater reliability for using TA on iOS or Android systems ranged from 0.987 to 0.989.

3.9. *ImitoWound (Switzerland 2020)*

ImitoWound is a digital wound management app provided by Imito company based in Zurich, Switzerland[44]. The app is compatible with both iOS and Android devices, and once a picture is taken, the app computes the wound size and reviews wound images on a timeline to assess the progress of wound healing, relying on calibration markers of standard size available on a PDF file. It's not regulated by the European Union MDR nor FDA since they state the application is intended for medical and medico-administrative documentation (storage & archival), communication, simple search and data representation/embellishment.

The database size and the exact segmentation technique are not revealed. But there are published data regarding the ICC reliability: Bayoumi et al. reported an ICC of 0.99 (95% C.I 0.998-0.999) on measuring lower limb chronic wounds of 61 patients, while Guarro et al. reported an ICC of 0.95 on 32 wound case series[45]. Moreover, Biagioni et al. published a study where they compared 85 wounds on toes, feet and legs caused by vascular disease measured with Imito and ImageJ[46]: the ICCs comparing the results were 0.995 for iOS (95% CI, 0.991-0.997) and 0.970 for android (95% CI, 0.946-0.984). Further studies have been published on the app ecosystem provided by the same company[47,48]. The developers state that in the future, the app could be utilised to evaluate the tissue characteristics of wounds and aid in making treatment decisions.

3.10. *WoundsWiseIQ (USA, 2015)*

WoundWiseIQ, released by Med-Compliance IQ, Inc. in 2015, is a mobile application for capturing wound images that is compatible with iOS devices[49]. The technology enables us to automatically calculate wound analysis colour differences, but the algorithm is declared to be patented and undisclosed. It is FDA-registered and HIPAA-compliant.

It consists of two mobile applications. The first one is used by clinicians to capture wounds and access image analysis; the second one is made available for patients to take wound images on their own. The mobile application sends captured images to a HIPAA-compliant cloud server, where they are processed.

The 3D wound image analysis allows to automatically calculate wound depth and volume. The patented algorithm performs image analysis of the wound perimeter, square area, planimetric area, and various colors of the wound.

The WoundWiseIQ app currently lacks connectivity to other applications such as Wound EMR's or Enterprise EMR'S. Currently, advanced analytics for decision support and predictive analysis are in progress.

Data on the segmentation technique, database size and efficiency in wound recognition are not available. There are no studies that validate the use of WoundWiseIQ in clinical practice or its inter-reliability in comparison to standard wound assessment.

Table 1: This table summarises the key characteristics, segmentation techniques, and clinical validations of ten mobile applications developed for wound segmentation using artificial intelligence (AI). The table evaluates each app based on several criteria, including availability on mobile platforms, regulatory approval, published studies, segmentation methods, and reliability metrics. The apps are ranked according to their segmentation accuracy and the level of clinical validation available, providing an assessment of their potential utility in clinical practice.

4. Discussion

In recent years, the use of smartphones and mobile apps in clinical practice has increased considerably, not only due to their capability to capture high-resolution photographs but also for the ability to store medical information, monitor chronic conditions, and enhance care management[53]. In particular, mobile apps dedicated to skin injury detection and assessment are attracting growing interest for their ability to offer diagnostic and therapeutic support, thereby improving the quality of care for patients with acute and chronic skin ulcers[16].

The use of these tools has been made possible through the development of advanced artificial intelligence (AI) algorithms, deep learning, and convolutional neural networks (CNN). Artificial intelligence is defined as the ability of a machine to perform tasks that normally require human intellect, such as visual perception, speech recognition or decision-making[54]. Belonging to this field is deep learning, a sub-discipline of AI that relies on artificial neural networks with different levels of depth, enabling the model to automatically learn complex features from rough data. Convolutional neural networks (CNNs), a type of deep learning model particularly well-suited for image processing, can identify the most salient features through multiple layers of processing, mimicking the structure and function of the human brain[54].

Artificial intelligence methodologies show significant positive impacts and promising prospects in the field of wound care and management[55]: in fact, the application of AI and deep learning has facilitated the development of advanced tools for automatic segmentation and detection of clinical images. Segmentation involves dividing an image into relevant parts, such as the contours of a lesion or different tissue types, while detection focuses on identifying key features, such as edges or colour changes. With regard to wounds, this process enables the algorithms to recognise and analyse the various types of tissue present, such as epithelial tissue, granulation tissue, slough, and necrotic tissue[8]. Therefore, it automatically analyses the status of the lesion and provides an accurate assessment, eliminating the need for subjective manual analysis that may be influenced by the clinician's experience and environmental conditions.

The COVID-19 pandemic has significantly accelerated the development of apps focused on skin lesion management, as they facilitate remote assessment[56]. Some of these apps enable real-time storage, management, and sharing of clinical information while also employing algorithms that can automate and standardise skin lesion assessments. They also promote greater diagnostic consistency among different healthcare providers, which is crucial, especially in settings where staff training and experience may differ.

Through this literature review, we aim to present the main automated assessment tools available on the market to healthcare professionals. Significant advantages are recognised from the use of these applications, such as the standardisation of assessment and improved diagnostic accuracy, which helps mitigate the subjective variability among operators. In addition, they help reduce the time of ulcer diagnosis and measurement compared to traditional methods[37]. Moreover, with the added benefit of remote assessment, they eliminate direct contact with the patient, reducing the risk of infection and avoiding pain, unlike traditional measurement techniques that involve using a paper ruler or graph paper[57,58].

Standardisation of diagnostic processes not only reduces the risk of human error but also enhances the tracking of injury progression over time. In addition, apps can serve as valuable support tools for less experienced staff by offering preliminary diagnoses and therapeutic suggestions, thereby improving the overall quality of care.

However, there are several limitations associated with the use of these tools. The review revealed that it was not possible to assess the algorithm's level of learning due to the lack of sufficiently large and diverse public databases for effective training. In addition, the existing scientific literature validating many of these apps is still limited, with published studies often featuring a small number of images, which limits the external validity of the results.

Most app developers do not provide adequate technical details regarding the deep learning algorithms employed or the data used for training these models, making it challenging to evaluate the actual effectiveness of the apps in diverse clinical settings. In addition, assessing the quality of mobile applications proved difficult due to their unavailability in major digital stores. In this context,

the literature suggests using the Mobile App Rating Scale (MARS) as an evaluation tool, which comprises five main criteria: engagement, functionality, aesthetics, information, and subjective quality[59].

Research in this field is continuously advancing, aiming to integrate automated skin injury assessments into routine clinical practice. In this context, a significant innovation is the development of a fully automated model capable of identifying and segmenting wound areas, as well as automatically assessing clinical severity from smartphone-acquired images. This approach utilises active semi-supervised learning to train a convolutional neural network model[60]. The model was subsequently trained and compared to PWAT scores, achieving a Spearman correlation coefficient of 0.85, indicating strong predictive accuracy[61].

Despite the many advantages of using these apps, concerns about data privacy, security, and integration with existing healthcare systems must be addressed [62]. As these apps collect sensitive clinical information and personal patient images, it is essential to ensure that data are protected in accordance with current regulations, such as the General Data Protection Regulation (GDPR) in Europe, Regulation (EU) 2016/679[63].

Despite the various challenges still to be addressed with automated mobile applications, future prospects look promising. Indeed, it is expected that algorithms will be soon able of automatically identifying the wound aetiology, offering accurate classification and recommending the most appropriate treatment and type of dressing. In this context, a learning model has recently been introduced that classifies wounds into the following categories: deep, infected, arterial, venous and pressure wounds[64–66].

Finally, deep learning is a key area of active research in wound image analysis, particularly in image classification, detection, and segmentation, which can significantly enhance diagnostic efficiency for healthcare providers[67]. The advancement of this technology could be especially valuable in addressing the needs of regions where expertise and access to healthcare services are limited.

Nevertheless, it remains essential to develop robust algorithms capable of analysing images captured in suboptimal conditions, such as poor lighting and inaccurate positioning[68].

As mobile applications for wound care continue to evolve in clinical practice, they have the potential to significantly enhance and improve patient care. Therefore, it is crucial to implement and promote the development of digital skills throughout the training and professional development of healthcare practitioners [69].

## 5. Conclusions

Mobile apps for skin wound management, powered by artificial intelligence and deep learning, are revolutionising the field of wound care and serve as valuable advanced tools for wound diagnosis and treatment to date. Despite the many advantages in standardisation, accuracy, and speed, some challenges persist, including a lack of adequate public databases, limited clinical validation, and concerns regarding data security. However, as algorithms advance and technologies become integrated into daily clinical practice, these apps have the potential to significantly enhance the quality of wound management and care, offering even more efficient support for wound care professionals.

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## References

1. Olsson M, Järbrink K, Divakar U, Bajpai R, Upton Z, Schmidtchen A, et al. The humanistic and economic burden of chronic wounds: A systematic review. *Wound Repair Regen.* gennaio 2019;27(1):114–25.
2. Martinengo L, Olsson M, Bajpai R, Soljak M, Upton Z, Schmidtchen A, et al. Prevalence of chronic wounds in the general population: systematic review and meta-analysis of observational studies. *Ann Epidemiol.* gennaio 2019;29:8–15.
3. Smet S, Verhaeghe S, Beeckman D, Fourie A, Beele H. The process of clinical decision-making in chronic wound care: A scenario-based think-aloud study. *Journal of Tissue Viability.* 1 maggio 2024;33(2):231–8.
4. Foltynski P, Ciechanowska A, Ladyzynski P. Wound surface area measurement methods. *Biocybernetics and Biomedical Engineering.* 1 ottobre 2021;41(4):1454–65.
5. Yee A, Harmon J, Yi S. Quantitative Monitoring Wound Healing Status Through Three-dimensional Imaging on Mobile Platforms. *J Am Coll Clin Wound Spec.* 2016;8(1–3):21–7.
6. Khoo R, Jansen S. The Evolving Field of Wound Measurement Techniques: A Literature Review. *Wounds.* giugno 2016;28(6):175–81.
7. Wang C, Yan X, Smith M, Kochhar K, Rubin M, Warren SM, et al. A unified framework for automatic wound segmentation and analysis with deep convolutional neural networks. In: 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 2015. p. 2415–8.
8. Le DTP, Pham TD. Unveiling the role of artificial intelligence for wound assessment and wound healing prediction. *Explor Med.* 31 agosto 2023;4(4):589–611.
9. Zhang R, Tian D, Xu D, Qian W, Yao Y. A Survey of Wound Image Analysis Using Deep Learning: Classification, Detection, and Segmentation. *IEEE Access.* 2022;10:79502–15.
10. Kermany DS, Goldbaum M, Cai W, Valentim CCS, Liang H, Baxter SL, et al. Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning. *Cell.* 22 febbraio 2018;172(5):1122–1131.e9.
11. Scebba G, Zhang J, Catanzaro S, Mihai C, Distler O, Berli M, et al. Detect-and-segment: A deep learning approach to automate wound image segmentation. *Informatics in Medicine Unlocked.* 1 gennaio 2022;29:100884.
12. Sorour SE, El-Mageed AAA, Albarrak KM, Alnaim AK, Wafa AA, El-Shafeiy E. Classification of Alzheimer's disease using MRI data based on Deep Learning Techniques. *Journal of King Saud University - Computer and Information Sciences.* 1 febbraio 2024;36(2):101940.
13. Anisuzzaman D m., Wang C, Rostami B, Gopalakrishnan S, Niezgoda J, Yu Z. Image-Based Artificial Intelligence in Wound Assessment: A Systematic Review. *Advances in Wound Care.* dicembre 2022;11(12):687–709.
14. Poon TWK, Friesen MR. Algorithms for Size and Color Detection of Smartphone Images of Chronic Wounds for Healthcare Applications. *IEEE Access.* 2015;3:1799–808.
15. Koepp J, Baron MV, Martins PRH, Brandenburg C, Kira ATF, Trindade VD, et al. The Quality of Mobile Apps Used for the Identification of Pressure Ulcers in Adults: Systematic Survey and Review of Apps in App Stores. *JMIR mHealth and uHealth.* 16 giugno 2020;8(6):e14266.
16. Shamloul N, Ghias MH, Khachemoune A. The Utility of Smartphone Applications and Technology in Wound Healing. *Int J Low Extrem Wounds.* settembre 2019;18(3):228–35.
17. Healthy.io | Digital wound management [Internet]. [citato 30 settembre 2024]. Disponibile su: <https://healthy.io/services/wound/>
18. Nussbaum SR, Carter MJ, Fife CE, DaVanzo J, Haught R, Nusgart M, et al. An Economic Evaluation of the Impact, Cost, and Medicare Policy Implications of Chronic Nonhealing Wounds. *Value Health.* gennaio 2018;21(1):27–32.
19. Sen CK. Human Wounds and Its Burden: An Updated Compendium of Estimates. *Adv Wound Care (New Rochelle).* 1 febbraio 2019;8(2):39–48.
20. Keegan AC, Bose S, McDermott KM, Starks White MP, Stonko DP, Jeddah D, et al. Corrigendum: Implementation of a patient-centered remote wound monitoring system for management of diabetic foot ulcers. *Front Endocrinol [Internet].* 23 giugno 2023 [citato 30 settembre 2024];14. Disponibile su: <https://www.frontiersin.org/journals/endocrinology/articles/10.3389/fendo.2023.1235970/full>
21. Keegan AC, Bose S, McDermott KM, Starks White MP, Stonko DP, Jeddah D, et al. Implementation of a patient-centered remote wound monitoring system for management of diabetic foot ulcers. *Front Endocrinol (Lausanne).* 2023;14:1157518.
22. Kivity S, Rajuan E, Arbeli S, Alcalay T, Shiri L, Orvieto N, et al. Optimising wound monitoring: Can digital tools improve healing outcomes and clinic efficiency. *Journal of Clinical Nursing.* 2024;33(10):4014–23.



23. Wound Imaging Solutions - WoundVision [Internet]. [citato 30 settembre 2024]. Disponibile su: <https://woundvision.com/>
24. Langemo D, Spahn J, Snodgrass L. Accuracy and Reproducibility of the Wound Shape Measuring and Monitoring System. *Adv Skin Wound Care*. luglio 2015;28(7):317–23.
25. Langemo D, Spahn J, Spahn T, Pinnamaneni VC. Comparison of standardized clinical evaluation of wounds using ruler length by width and Scout length by width measure and Scout perimeter trace. *Adv Skin Wound Care*. marzo 2015;28(3):116–21.
26. Wu W, Yong KYW, Federico MAJ, Gan SKE. The APD Skin Monitoring App for wound monitoring: Image processing, area plot, and colour histogram. *spamd* [Internet]. 2019 [citato 30 settembre 2024]; Disponibile su: <https://scienceopen.com/hosted-document?doi=10.30943/2019/28052019>
27. Tang M, Gorelick L, Veksler O, Boykov Y. GrabCut in One Cut. In 2013 [citato 30 settembre 2024]. p. 1769–76. Disponibile su: [https://openaccess.thecvf.com/content\\_iccv\\_2013/html/Tang\\_GrabCut\\_in\\_One\\_2013\\_ICCV\\_paper.html](https://openaccess.thecvf.com/content_iccv_2013/html/Tang_GrabCut_in_One_2013_ICCV_paper.html)
28. Gupta S, Girshick R, Arbeláez P, Malik J. Learning Rich Features from RGB-D Images for Object Detection and Segmentation. In: Fleet D, Pajdla T, Schiele B, Tuytelaars T, curatori. *Computer Vision – ECCV 2014*. Cham: Springer International Publishing; 2014. p. 345–60.
29. Nair HKR. Increasing productivity with smartphone digital imagery wound measurements and analysis. *J Wound Care*. 1 settembre 2018;27(Sup9a):S12–9.
30. Clinicgram – The revolutionary app that allows you to diagnose diseases with your smartphone. [Internet]. [citato 30 settembre 2024]. Disponibile su: <https://www.clinicgram.com/>
31. Swift Skin and Wound Mobile App and Dashboards [Internet]. Swift. [citato 30 settembre 2024]. Disponibile su: <https://swiftmedical.com/solution/>
32. Wang SC, Anderson JAE, Evans R, Woo K, Beland B, Sasseville D, et al. Point-of-care wound visioning technology: Reproducibility and accuracy of a wound measurement app. *PLOS ONE*. 17 agosto 2017;12(8):e0183139.
33. Ramachandram D, Ramirez-GarciaLuna JL, Fraser RDJ, Martínez-Jiménez MA, Arriaga-Caballero JE, Allport J. Fully Automated Wound Tissue Segmentation Using Deep Learning on Mobile Devices: Cohort Study. *JMIR mHealth and uHealth*. 22 aprile 2022;10(4):e36977.
34. Redmon J, Farhadi A. YOLOv3: An Incremental Improvement [Internet]. arXiv; 2018 [citato 5 ottobre 2024]. Disponibile su: <http://arxiv.org/abs/1804.02767>
35. Liu Z, Agu E, Pedersen P, Lindsay C, Tulu B, Strong D. Chronic Wound Image Augmentation and Assessment Using Semi-Supervised Progressive Multi-Granularity EfficientNet. *IEEE Open Journal of Engineering in Medicine and Biology*. 2023;1–17.
36. EfficientNetB0 - Furiosa Models [Internet]. [citato 5 ottobre 2024]. Disponibile su: [https://furiosa-ai.github.io/furiosa-models/latest/models/efficientnet\\_b0/](https://furiosa-ai.github.io/furiosa-models/latest/models/efficientnet_b0/)
37. Au Y, Beland B, Anderson JAE, Sasseville D, Wang SC. Time-Saving Comparison of Wound Measurement Between the Ruler Method and the Swift Skin and Wound App. *J Cutan Med Surg*. 1 marzo 2019;23(2):226–8.
38. CARES4WOUNDS Wound Management System | Tetsuyu Healthcare [Internet]. Tetsuyu Healthcare. [citato 5 ottobre 2024]. Disponibile su: <https://tetsuyuhealthcare.com/solutions/wound-management-system/>
39. Chan KS, Chan YM, Tan AHM, Liang S, Cho YT, Hong Q, et al. Clinical validation of an artificial intelligence-enabled wound imaging mobile application in diabetic foot ulcers. *Int Wound J*. gennaio 2022;19(1):114–24.
40. Kitamura A, Nakagami G, Okabe M, Muto S, Abe T, Doorenbos A, et al. An application for real-time, remote consultations for wound care at home with wound, ostomy and continence nurses: a case study. *Wound Practice and Research* [Internet]. 1 settembre 2022 [citato 5 ottobre 2024];30(3). Disponibile su: <https://journals.cambridgemedia.com.au/wpr/volume-30-number-3/application-real-time-remote-consultations-wound-care-home-wound-ostomy-and-continence-nurses-case-study>
41. Home [Internet]. Tissue Analytics. 2020 [citato 5 ottobre 2024]. Disponibile su: <https://www.tissue-analytics.com/>
42. Barakat-Johnson M, Jones A, Burger M, Leong T, Frotjold A, Randall S, et al. Reshaping wound care: Evaluation of an artificial intelligence app to improve wound assessment and management amid the COVID-19 pandemic. *Int Wound J*. ottobre 2022;19(6):1561–77.
43. Fong KY, Lai TP, Chan KS, See IJL, Goh CC, Muthuveerappa S, et al. Clinical validation of a smartphone application for automated wound measurement in patients with venous leg ulcers. *Int Wound J*. marzo 2023;20(3):751–60.
44. Wound Assessment Tool - imitoWound App [Internet]. imito AG. [citato 5 ottobre 2024]. Disponibile su: <https://imito.io/en/imitowound>

45. Guarro G, Cozzani F, Rossini M, Bonati E, Del Rio P. Wounds morphologic assessment: application and reproducibility of a virtual measuring system, pilot study. *Acta Biomedica Atenei Parmensis*. 3 novembre 2021;92(5):e2021227.
46. Schroeder AB, Dobson ETA, Rueden CT, Tomancak P, Jug F, Eliceiri KW. The ImageJ ecosystem: Open-source software for image visualization, processing, and analysis. *Protein Sci*. gennaio 2021;30(1):234–49.
47. Sia DK, Mensah KB, Opoku-Agyemang T, Folitse RD, Darko DO. Mechanisms of ivermectin-induced wound healing. *BMC Vet Res*. 20 ottobre 2020;16:397.
48. Khac AD, Jourdan C, Fazilleau S, Palayer C, Laffont I, Dupeyron A, et al. mHealth App for Pressure Ulcer Wound Assessment in Patients With Spinal Cord Injury: Clinical Validation Study. *JMIR mHealth and uHealth* [Internet]. febbraio 2021 [citato 5 ottobre 2024];9(2). Disponibile su: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7943335/>
49. WoundWiseIQ – Image Analytics. Improved Outcomes. [Internet]. [citato 5 ottobre 2024]. Disponibile su: <https://woundwiseiq.com/>
50. Phung SL, Bouzerdoun A, Chai D. Skin segmentation using color pixel classification: analysis and comparison. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. gennaio 2005;27(1):148–54.
51. Kuang B, Pena G, Szpak Z, Edwards S, Battersby R, Cowled P, et al. Assessment of a smartphone-based application for diabetic foot ulcer measurement. *Wound Repair and Regeneration*. 2021;29(3):460–5.
52. Younis PHM, El Sebaie AEM, Waked IS, Bayoumi MBI. Validity And Reliability of a Smartphone Application in Measuring Surface Area of Lower Limb Chronic Wounds. *The Egyptian Journal of Hospital Medicine* [Internet]. 1 ottobre 2022 [citato 5 ottobre 2024]; Disponibile su: [https://journals.ekb.eg/article\\_270504.html](https://journals.ekb.eg/article_270504.html)
53. El-Rashidy N, El-Sappagh S, Islam SMR, M. El-Bakry H, Abdelrazek S. Mobile Health in Remote Patient Monitoring for Chronic Diseases: Principles, Trends, and Challenges. *Diagnostics (Basel)*. 29 marzo 2021;11(4):607.
54. Ohura N, Mitsuno R, Sakisaka M, Terabe Y, Morishige Y, Uchiyama A, et al. Convolutional neural networks for wound detection: the role of artificial intelligence in wound care. *J Wound Care*. 1 ottobre 2019;28(Sup10):S13–24.
55. Dabas M, Schwartz D, Beeckman D, Gefen A. Application of Artificial Intelligence Methodologies to Chronic Wound Care and Management: A Scoping Review. *Adv Wound Care (New Rochelle)*. aprile 2023;12(4):205–40.
56. Kim PJ, Homsy HA, Sachdeva M, Mufti A, Sibbald RG. Chronic Wound Telemedicine Models Before and During the COVID-19 Pandemic: A Scoping Review. *Adv Skin Wound Care*. 1 febbraio 2022;35(2):87–94.
57. Foltynski P, Ladyzynski P. Internet service for wound area measurement using digital planimetry with adaptive calibration and image segmentation with deep convolutional neural networks. *Biocybernetics and Biomedical Engineering*. 1 gennaio 2023;43(1):17–29.
58. Lucas Y, Niri R, Treuillet S, Douzi H, Castaneda B. Wound Size Imaging: Ready for Smart Assessment and Monitoring. *Adv Wound Care (New Rochelle)*. novembre 2021;10(11):641–61.
59. Stoyanov SR, Hides L, Kavanagh DJ, Zelenko O, Tjondronegoro D, Mani M. Mobile app rating scale: a new tool for assessing the quality of health mobile apps. *JMIR Mhealth Uhealth*. 11 marzo 2015;3(1):e27.
60. Curti N, Merli Y, Zengarini C, Giampieri E, Merlotti A, Dall'Olio D, et al. Effectiveness of Semi-Supervised Active Learning in Automated Wound Image Segmentation. *International Journal of Molecular Sciences*. gennaio 2023;24(1):706.
61. Curti N, Merli Y, Zengarini C, Starace M, Rapparini L, Marcelli E, et al. Automated Prediction of Photographic Wound Assessment Tool in Chronic Wound Images. *J Med Syst*. 16 gennaio 2024;48(1):14.
62. Deniz-Garcia A, Fabelo H, Rodriguez-Almeida AJ, Zamora-Zamorano G, Castro-Fernandez M, Ruano M del PA, et al. Quality, Usability, and Effectiveness of mHealth Apps and the Role of Artificial Intelligence: Current Scenario and Challenges. *Journal of Medical Internet Research*. 4 maggio 2023;25(1):e44030.
63. General data protection regulation (GDPR) | EUR-Lex [Internet]. [citato 5 ottobre 2024]. Disponibile su: <https://eur-lex.europa.eu/EN/legal-content/summary/general-data-protection-regulation-gdpr.html>
64. Huang PH, Pan YH, Luo YS, Chen YF, Lo YC, Chen TPC, et al. Development of a deep learning-based tool to assist wound classification. *J Plast Reconstr Aesthet Surg*. aprile 2023;79:89–97.
65. Patel Y, Shah T, Dhar MK, Zhang T, Niezgoda J, Gopalakrishnan S, et al. Integrated image and location analysis for wound classification: a deep learning approach. *Sci Rep*. 25 marzo 2024;14(1):7043.
66. Malihi L, Hüsters J, Richter ML, Moelleken M, Przysucha M, Busch D, et al. Automatic Wound Type Classification with Convolutional Neural Networks. *Stud Health Technol Inform*. 29 giugno 2022;295:281–4.
67. Zhang P. Image Enhancement Method Based on Deep Learning. *Mathematical Problems in Engineering*. 2022;2022(1):6797367.
68. Chairat S, Chaichulee S, Dissaneewate T, Wangkulangkul P, Kongpanichakul L. AI-Assisted Assessment of Wound Tissue with Automatic Color and Measurement Calibration on Images Taken with a Smartphone. *Healthcare (Basel)*. 16 gennaio 2023;11(2):273.

69. Gagnon J, Probst S, Chartrand J, Lalonde M. Self-supporting wound care mobile applications for nurses: A scoping review protocol. *J Tissue Viability*. febbraio 2023;32(1):79–84.

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