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Review Article

Progress in the application of artificial intelligence in skin wound assessment and prediction of healing time

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Abstract: Since the 1970s, artificial intelligence (AI) has played an increasingly pivotal role in the medical field, enhancing the efficiency of disease diagnosis and treatment. Amidst an aging population and the proliferation of chronic disease, the prevalence of complex surgeries for high-risk multimorbid patients and hard-to-heal wounds has escalated. Healthcare professionals face the challenge of delivering safe and effective care to all patients concurrently. Inadequate management of skin wounds exacerbates the risk of infection and complications, which can obstruct the healing process and diminish patients' quality of life. AI shows substantial promise in revolutionizing wound care and management, thus enhancing the treatment of hospitalized patients and enabling healthcare workers to allocate their time more effectively. This review details the advancements in applying AI for skin wound assessment and the prediction of healing timelines. It emphasizes the use of diverse algorithms to automate and streamline the measurement, classification, and identification of chronic wound healing stages, and to predict wound healing times. Moreover, the review addresses existing limitations and explores future directions.

Keywords: Skin wound healing, artificial intelligence, skin wound measurement, skin wound classification, burn degree assessment, chronic wound prediction

Introduction

Artificial intelligence (AI) encompasses computer algorithms designed to mimic human cognitive function [1, 2]. Since the 1970s, AI technologies such as machine learning (ML), neural networks, semantic recognition, and image analysis have become integral to the medical field, substantially enhancing the diagnosis and treatment of diseases [3]. In the 21st century, fueled by advancements in deep learning (DL), ML algorithms, hardware, and data storage capabilities, AI has undergone a significant evolution, offering profound support in clinical settings [4].

In clinical practice, skin wounds are frequently encountered [5], necessitating that clinicians base their treatment decisions and assessments of wound healing progress on various factors, including wound size, classification, and tissue composition [6]. These assessments largely depend on the subjective visual evaluations of physicians and clinical staff [7, 8], highlighting an opportunity to integrate emerging technologies [9]. Inaccurate evaluation can result in serious consequences such as improper dressing selection, overlooked non-healing wounds, and delayed specialist referrals [10]. With the increasing number of surgeries involving high-risk and multimorbid patients, effective perioperative wound management becomes critical [11]. AI is not only valuable for surgical wounds but also offers significant benefits for assessing healing times in chronic and burn wounds [9, 12]. Inadequate skin wound management heightens the risk of surgical site infections and other complications [11]. Additionally, patients with chronic wounds often require intricate care due to comorbidities that complicate the healing process [13].

Numerous articles have explored the use of imaging techniques for skin wounds, yet there remains a notable gap in the systematic sum-

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marization of innovative AI methodologies and their applications in this domain [14]. The forefront of recent advancements in AI - particularly over the last three years - has been dominated by machine learning (ML) and deep learning (DL) [15]. AI facilitates the rapid analysis of vast arrays of wound images, working in tandem with intelligent algorithms and extensive databases to accurately identify, classify, and predict wound tissue characteristics. Importantly, AI has the ability to improve accuracy through ongoing learning. Despite the availability of seemingly ample medical data sets and sophisticated algorithms for many years, there is still a significant lack of algorithms that meaningfully affect clinical care [16]. This review aims to provide a comprehensive overview of the current applications of AI in skin wound assessment and the prediction of healing times, setting the stage for future developments.

Skin wound assessment

Monitoring changes in wound surface area over several weeks is a critical metric for evaluating the effectiveness of therapeutic interventions [17]. Traditional methods of measuring wounds using a scalpel to gauge width and length are often imprecise, potentially resulting in less than optimal treatments and outcomes [18]. Artificial intelligence significantly enhances the precision of measuring wound dimensions, topology, edge positioning, and the percentage of different tissue types. This advancement markedly improves the accuracy of wound closure assessments in clinical settings. For instance, the Automatic Skin Ulcer Region Assessment framework developed by Daniel et al. efficiently segmented wounds and measured their sizes with a low error rate of 14% through a semi-automatic method [19]. Additionally, Zhao et al. created a vision-laser scanner, utilizing an artificial neural network, to reconstruct wounds' three-dimensional edges and topologies [20]. Jones et al. employed a Convolutional Neural Network (CNN) to determine epidermal and dermal thickness and the percentage of re-epithelialization [21], while Ramachandram et al. introduced a deep learning approach for objective tissue identification and measurement [22].

Traditionally, collecting and manually observing regular wound images to determine study metrics has been a time-consuming and laborious process. Furthermore, defining wound margins is often subjective and can vary among experts [23]. To overcome these challenges, Carrión et al. developed a deep learning (DL)-based image analysis pipeline capable of processing non-uniform wound images. This system extracts critical data such as key wound locations, performs image cropping, and calculates metrics related to the size of the wound periphery over time [23]. This pipeline facilitated a high-throughput assessment and accurate tracking of wound size. In their research, it provided essential details like wound closure percentages and dimensions for further analysis. The system proved effective with minimal human intervention and could accurately estimate wound sizes even when up to 50% of the reference images were absent.

To optimize the area selected for automated analysis, Wang et al. deployed support vector machines (SVM) to define wound boundaries precisely [24]. These boundaries were further refined through the application of the conditional random field method. Estimations of wound extent rely on optical theory, comparing images across color channels, and using a fuzzy spectral clustering segmentation algorithm to delineate the wound area [25]. These methods, however, are confined to two-dimensional imagery. To capture the three-dimensional architecture of wounds, Edward et al. used a vision-laser scanner to generate a 3D point cloud of the wound's edges and topology [20]. Integrating this scanner with gantry robots, as depicted in **Figure 1**, enhances accuracy and improves patient outcomesby reducing human error, lowering infection rates, and accelerating healing. Additionally, a custom-designed supplementary laser LED was employed to provide an extra measurement point, leveraging an artificial neural network to decrease scanning time [20]. In collaboration with RSI, Andreas Körber and his team connected digital photography with optical raster through a digital scanner and picture processing software (DigiSkin), achieving precise three-dimensional imaging of chronic wounds [26]. Moreover, Wang et al. developed an integrated system that combines visual features with deep learning algorithms for wound segmentation and area estimation, using a newly developed convolutional encoder-decoder network - a variant of ConvNet [18]. This sys-

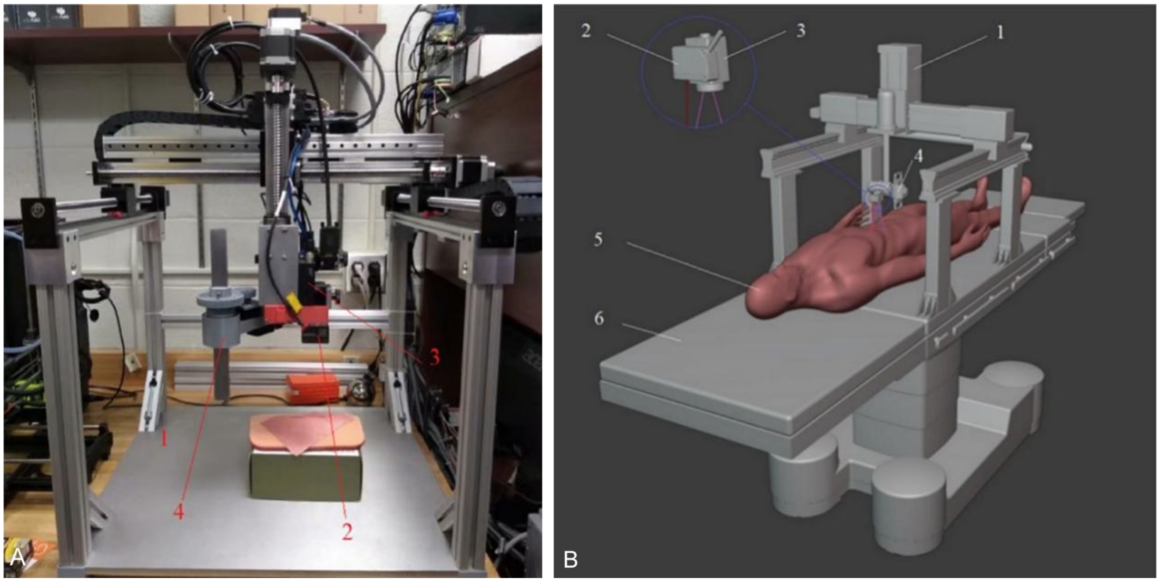

Figure 1. Gantry robotic wound closure system. A. Set configuration; B. Visionary sketch of setting in operating room. 1: gantry robot, 2: laser range sensor, 3: 2D camera, 4: fixture placement device, 5: patient body, 6: surgeon bed. Source: Zhao YM, Currie EH, Kavoussi L, Rabbany SY. Laser scanner for 3D reconstruction of a wound's edge and topology. International Journal of Computer Assisted Radiology and Surgery 2021; 16: 1761-1773 [20].

tem is not only computationally efficient and reliable but also includes capabilities for detecting wound infections and predicting healing outcome. The specific applications and benefits of these methods are detailed in **Table 1**.

The use of AI technology varies across different types of wounds. Commonly treated clinical skin wounds include lower extremity venous ulcers, diabetic foot ulcers, pressure ulcers, burn wounds, and surgically infected wounds. Integrating AI with computer vision and imaging technologies enables non-contact measurements, enhancing the regular monitoring of ulcer wounds [27]. This allows patients to send images of their wounds from their homes, reducing the need for frequent hospital visits. Moreover, leveraging data from electronic medical records combined with machine learning (ML) algorithms has proven highly effective in predicting the development of pressure ulcers [28]. AI systems can customize predictions based on unique patient data from medical records. In the context of burn wounds, AI-driven systems for assessing burn depth have demonstrated significant clinical value [29]. Additionally, Egberts et al. employed a neural network to predict the healing trajectory of burn wounds, successfully simulating skin contraction over periods longer than one year [30]. For surgical site infections (SSIs), ML algorithms trained with comprehensive health data, including detailed wound status descriptors, have effectively predicted SSI risks [31].

The integration of various optical wound assessment tools and multi-modal imaging devices has significantly improved the stability and precision of wound evaluations. These technological advancements provide detailed measurements of wound area and volume, and also yield insights into the tissue composition within the wound bed [32]. The ongoing development of intelligent information evaluation systems has greatly improved the ease and systematic management of digital imagery and wound-related data. This progress has paved the way for sophisticated intelligent monitoring systems, which play a crucial role in enhancing healing rates and expediting patient recovery [33].

Skin wound classification

Histologic classification of skin wounds

The variety of tissue types within a wound serves as a crucial indicator of its healing progress [22]. Precise analysis of wound tissue characteristics, such as the area and the percentage of granulation tissue (PGT), is essen-

Table 1. Comparison of AI methods regarding wound measurement

Wound Measurement Method	Principle	Application	Merits	Limitations
Automatic image analysis pipeline [23]	Computer vision, object detection algorithms (YOLO)	Automated measurement of wound size and automatic assessment of average wound closure percentage. High fidelity results on unseen data with minimal human intervention	Automated and enables high fidelity results	Not good at dealing with some of the challenges like occlusion and blur. Quantitative measurements are not exactly aligned
Fuzzy spectral clustering [25]	Gray scale based fuzzy similarity measure, spectral clustering segmentation algorithm	Accurate depiction of the wound area and automatic calculation of the contrast between wound and non-wound areas	Effective depiction of wound areas in non-uniformly illuminated images	The wounds that are near to heal or the images having very low (i.e. nearly zero) contrast between healed wound area and healthy skin are not accurately segmented. The method is not completely automatic.
Vision laser scanner [20]	Use laser ranging scanning to generate 3D point cloud, artificial neural network estimation method	Accurate 3D reconstruction of wound margins and topology	Simultaneous generation of 3D point clouds of wound skin and its edges	The scanner can only deal with small size wound (~3-inch length)
Integrated system [18]	Convolutional encoder-decoder networks (a variant of ConvNet), Hough transformation, computer vision tasks	Wound segmentation in an end-to-end different manner and estimation of wound surface area by transformation of pixel length to actual length	High computational efficiency, validity and reliability as a multifunctional, integrated and unified framework system	

tial for enhancing wound care and recovery [34]. Traditional histologic analysis, commonly used for disease diagnosis, requires extensive and time-consuming tissue preparation [35]. To address this, Howell et al. developed an AI-based tool for both qualitative and quantitative wound assessment. They benchmarked this tool against human expert evaluations, establishing a reliable AI framework to measure wound area and PGT [36]. Further exploring tissue pathology, Maknuna et al. introduced a rapid method for characterizing scar lesions in H&E-stained tissues [23]. They utilized both supervised and unsupervised learning approaches to teach the computer to identify patterns and extract insights from unclassified data [37, 38]. Their use of the K-means algorithm enabled detailed analysis of features like collagen density and its directional variance, confirming a substantial 50% difference between normal and scar tissue. This method proves effective for delineating scar tissue's pathologic attributes and aiding in the formulation of targeted treatment strategies [37]. Additionally, AI medical devices have enhanced the precision of remote wound assessment and classification [39].

Beyond the measurement tools previously mentioned, several researchers have explored the application of Convolutional Neural Networks (CNN) in wound assessment. Utilizing deep learning techniques, they have effectively identified and segmented unique features within image regions. Since its adoption in 2012, CNNs have been extensively applied across various biomedical fields, showcasing its proficiency in classifying and segmenting large volumes of image data swiftly and accurately [40, 41]. Specifically for skin wounds, segmentation involves precisely outlining the wound area in the image and isolating the necessary components for analysis. To enhance the quantitative analysis of skin wound histology, Jones et al. developed a CNN capable of automatically calculating parameters such as wound depth, wound width, as well as the thicknesses of epidermal and dermal layers, and the percentage of re-epithelialization [21]. This CNN proved its efficacy by accurately segmenting entire sections of H&E-stained wounds on a pixel-wise level in under 30 seconds using a standard desktop computer. These technological advances set the stage for more detailed quantification of histologic features in wound imagery.

Burn degree assessment

Precise assessment of burn severity is critical for effective wound care and treatment [42]. An erroneous evaluation can result in delayed wound management, adversely affecting future treatment outcomes [43]. In contemporary medical practices, artificial intelligence (AI) is utilized to assess burn severity by estimating the total body surface area affected, depth of burns, and extent of scarring [44]. Additionally, Spatial Frequency-Domain Imaging (SFDI) technology, which leverages the relationship between histologic observations and tissue property changes, has proven to be an invaluable tool. This technology can predict the severity of burns within a 24-hour period by analyzing images captured at various wavelengths and frequencies [45-47]. The use of Support Vector Machine (SVM) classifiers further enhances the precision of these predictions [48].

Concurrently, Cirillo et al. showcased the effectiveness of AI in determining burn depth [49]. Using semantic segmentation of images from polarized high-performance light cameras, their AI model proficiently identified four distinct levels of burn severity [50]: superficial (I), superficial to intermediate (II), medium to deep (III), and deep to full thickness (IV), achieving remarkable accuracy rates of up to 92% [49]. Constructing such a model requires extensive learning and training, supported by a substantial training dataset. Nevertheless, the prospects for further refining the algorithm through the acquisition of more images are both viable and promising for future advancements [49, 51].

Skin wound prediction

Chronic wound prediction

Chronic wounds pose a significant global challenge, defined by localized skin and tissue injuries with a compromised physiologic healing response [25, 52]. The Wound Healing Association describes chronic wounds as a failure to restore the normal structure and function of damaged tissue in a regular and timely manner [53]. Typically, the healing process for chronic wounds extends beyond four weeks, significantly impairing affected individuals' quality of life and well-being, and contributing to elevated mortality rates [54]. Therefore, precise assessment, prediction, and management of chronic wounds are crucial for reducing the healthcare system's lburden and enhancing the speed and quality of patient recovery [55].

In clinical practice, common lower extremity wounds such as arterial, diabetic, pressure, and venous ulcers [56] pose a high risk to older adults, who are more susceptible due to various age-related changes [57]. These changes include an increased prevalence of chronic conditions like cardiovascular disease and diabetes, along with impaired mobility, incontinence, low weight, poor nutritional status, and cognitive impairment [58].

Age-related intrinsic alterations in skin wound healing - such as modified inflammatory responses, reduced levels of supportive extracellular matrix (ECM) and growth factors, delayed epithelialization, and diminished angiogenic activity - contribute to slower wound closure rates in older adults [59]. With the aging population, the incidence of such wounds has significantly increased, intensifying the demand on limited healthcare resources [60]. To address this, researchers have developed an AI-powered wearable sensor linked with advanced wound dressing bandages. This system uses a deep artificial neural network (ANN) algorithm for monitoring chronic wounds and identifying their healing stages [61]. This near-field sensing technology provides critical data for treatment decisions and assesses the effectiveness of wound care medications. Within the realm of telemedicine, Chakraborty et al. have introduced a model that uses Linear Discriminant Analysis to classify tissue types, achieving a tissue prediction accuracy of 91.45% [62]. This approach enables remote diagnosis of chronic wound healing statuses, aiding clinicians in making more informed decisions based on quantitative tissue composition data. Moreover, advancements in statistical computing have propelled the development of several promising machine learning techniques [63]. Jung et al. utilized modern ML methods to create a predictive model for delayed wound healing, training it with collected wound data to enable early and precise predictions of delayed healing outcomes [64].

Chronic wounds represent a significant global health challenge, where accurate diagnosis and effective treatment are crucial for facilitating healing and averting further complications [65]. In the healthcare sector, AI is increasingly utilized to analyze medical data predictively, adapting seamlessly to new information [66]. Although electronic medical records are extensively used for documenting wounds, managing and tracking every aspect of patient care for those with chronic wounds is still a complex task [67]. Nonetheless, leveraging big data analytics and machine learning offers substantial promise in reducing treatment costs, decreasing the time needed for simulations, and enhancing the overall quality of care [68].

Wound healing time prediction

The ability to predict wound healing time holds significant clinical value, enabling physicians to swiftly tailor treatment plans to individual needs [69]. Through accurate predictions, doctors can decide whether a patient requires multiple debridements or if early closure is feasible, as well as determine the best timing for closing traumatic wounds. This predictive capability not only reduces the duration to wound closure but also minimizes the risk of wound complications and failures [70].

Assessing the thickness of the epidermis and scabs is critical for understanding the skin wound healing process, as it provides key insights into the normalcy of the re-epithelialization process [71-73]. Optical Coherence Tomography (OCT), a real-time, non-invasive imaging technique, enables the cross-sectional evaluation of tissue microstructures. Integrating OCT with AI algorithms allows for the automated measurement of the thickness of epithelial tissues and scabs, thereby facilitating predictions about wound healing times [74]. Predicting the healing of amputation wounds, however, remains a complex challenge due to factors such as severe ischemia and the absence of reliable assessment tools. To address this, Squiers et al. implemented a novel imaging system to capture multispectral images of the lower extremities [75]. Analyzing these images in conjunction with patient clinical risk factors through machine learning algorithms has enhanced the accuracy of predictions regarding amputation wound healing. Additionally, this approach potentially reduces the necessity for reoperations and the occurrence of delayed healing.

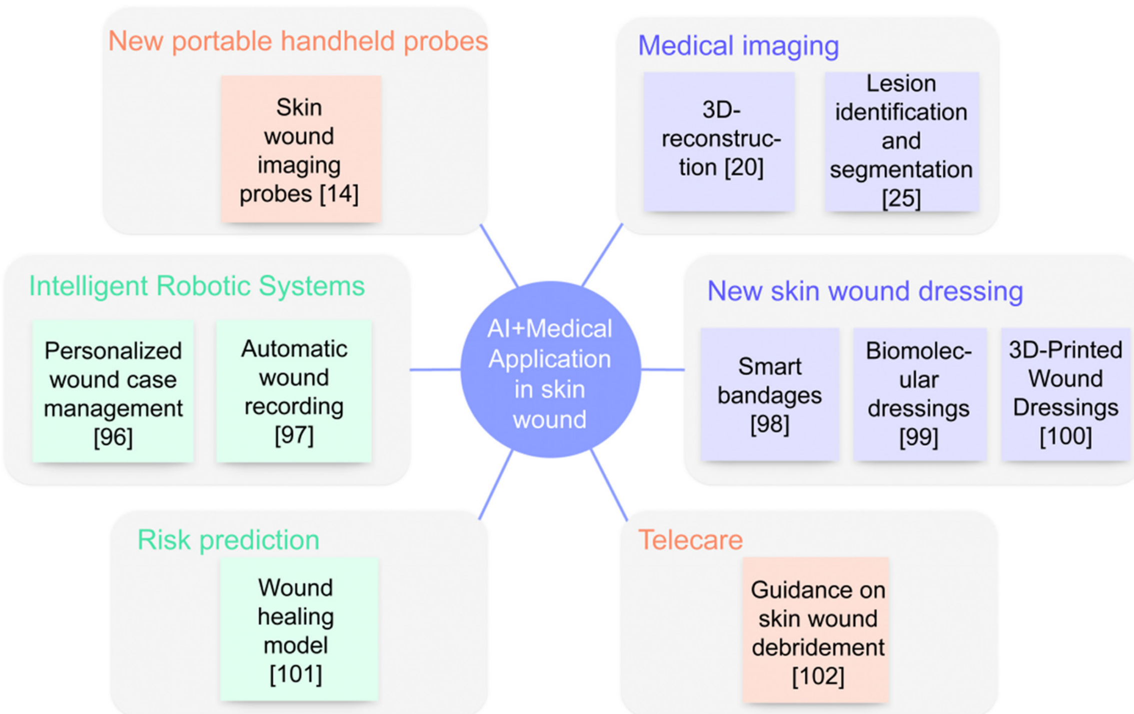

Figure 2. AI+ Medical application scenarios in skin wounds. Scenarios for the use of AI in skin wounds, including a variety of novel imaging techniques, risk prediction systems incorporating algorithms, intelligent robotics, and the accompanying promise of telemedicine and personalized medicine.

In 2020, Chinese researchers developed a CNN-based artificial model to recognize burn depth, which was effectively used to predict the healing time of burn wounds. This model accurately estimated the wound healing timeline by analyzing the depth of the burn [76].

Wound healing is a complex and dynamic process, making the accurate prediction of healing times a persistent challenge for clinicians. However, with the growing accessibility of vast data sets and enhanced computing capabilities, AI-based models are poised to play a crucial role in the prediction and assessment of wound healing timelines [77].

Summary and outlook

Currently, AI is evolving at an unprecedented pace, particularly in the medical sector where it significantly enhances rapid image interpretation, diagnosis, risk prediction, and adjuvant treatment [78, 79]. Specific examples of AI applications in skin wound management are illustrated in **Figure 2**. Over the last decade, the swift advancement of computer processing technology has facilitated the deeper integration of AI systems across various medical imaging technologies such as X-ray, ultrasound, computed tomography, and magnetic resonance imaging [77]. Machine learning (ML) and deep learning (DL) have been instrumental in analyzing medical images from these technologies, demonstrating high accuracy and reliability [80]. AI's capabilities extend across a broad spectrum of functions, including assisting in diagnosis, selecting therapies, predicting risks, stratifying diseases, reducing medical errors, and enhancing productivity [81]. In a notable study, Aaron Jones et al. implemented a quasi-experimental design across four settings within the Australian Health Service. They gathered data from standard and intervention groups, revealing that 101 out of 132 wounds showed improvement during the intervention, with a mean wound size reduction of 53.99%. This research underscores the practicality and effectiveness of AI in wound management [82].

Despite the advancements, challenges remain from the tedious and time-consuming processes involved in wound image collection, classification, and interpretation, compounded by the lack of robust and efficient data analysis systems [83]. A primary barrier is data availability; hospitals often hesitate to share data due to privacy concerns [84], while machine learning (ML) requires extensive datasets for effective training, often difficult to secure [85]. Advancements in algorithms and the broader adoption of cloud computing may mitigate these issues [86], and stricter data privacy regulations could also provide support [87]. Another significant challenge is the clinical implementation of AI, with limited empirical evidence on its impact on patient outcome [88]. Moreover, AI interventions should expedite, not hinder, medical processes, including the necessary training for healthcare providers [89]. Ethical concerns also persist, as poor decisions in healthcare can lead to severe repercussions, and accountability remains a critical issue [90]. The legal complexities associated with applying traditional tort liability to AI technologies due to their opaque and unpredictable nature call for innovative legal standards and models, such as AI personhood or joint liability, to establish a fair and predictable framework for AI-related medical malpractice [91].

The future of AI in skin wound management looks promising, particularly with the advent of Explainable Artificial Intelligence (XAI) based on deep learning (DL) in medical image analysis. XAI is evolving as a vital tool that enhances AI's ability to offer novel insight into data, thereby enriching the resource base with new discovery elements [92]. As DL-based methods become more widespread, the demand for explainability increases, especially in critical areas such as medical image analysis, which plays a crucial role in skin wound assessment [93]. Beyond diverse imaging techniques and AI-integrated systems, AI-powered remote consultation systems using smartphones and tablets for data gathering and connectivity are gaining traction [94]. For instance, recent advancements in AI technologies have improved the remote monitoring of diabetic foot ulcers by mobile applications [95]. Digital solutions for the remote diagnosis and monitoring of wounds in community settings have rapidly evolved. The COVID-19 pandemic has further spurred the research and development of these innovative technologies. Applying ML algorithms in diagnosing and managing chronic wounds presents a viable strategy to enhance the care of hospitalized patients while optimizing the efficiency of healthcare professionals [12]. With extensive and diverse predictors and data sets, ML becomes an invaluable tool for stratifying risk among patients with a predisposition to chronic wounds [63]. The move towards personalized telemedicine is shaping up to deliver optimal patient outcomes, and with the development of intelligent robotic systems, the dawn of AI-driven personalized telemedicine appears imminent [1].

AI has dramatically transformed the field of wound care, revolutionizing the assessment, measurement, classification, and prediction of wounds. At present, AI applications in skin wounds mainly concentrate on two areas: wound image analysis and data integration [96]. However, the development of AI-based systems to a level suitable for clinical use, ensuring the delivery of high-quality wound care, is still underway [79]. By setting stringent standards for wound data collection and creating more user-friendly and efficient recording systems, AI is poised to significantly enhance wound care practice [97-102]. This will provide patients with a more comprehensive and higher-quality care experience.

Disclosure of conflict of interest

None.

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