Advances in Bioresearch
Adv. Biores., Vol 16 (3) May 2025: 231-236

Print ISSN 0976-4585; Online ISSN 2277-1573
Journal's URL:http://www.soeagra.com/abr.html
CODEN: ABRDC3
DOI: 10.15515/abr.0976-4585.16.3.231236

Advances in Bioresearch

REVIEW ARTICLE

Role of Artificial Intelligence in Wound Healing

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ABSTRACT
The patient features at the wound level, biological, environmental, and socioeconomic factors all play a part in the complex and dynamic process of healing wounds. Haemostasis, inflammatory response, proliferation, and remodelling are all parts of its mechanism. An assessment of the wound's angiogenesis, inflammation, mesh of connective tissue restoration contracture of the wound, remodelling, and re-emphasizing would provide information about the process of recovery. Research on wounds requires an understanding of important factors in the healing process. Artificial intelligence has the potential to be a beneficial tool in improving the complex process of wound healing, which is influenced by a multitude of factors. The application of artificial intelligence (AI) in wound healing, including diagnosis, therapy, planning, monitoring, and predictive analytics, is examined in this comprehensive review. A variety of AI methods such as computer vision, profound understanding and machine learning, are covered in this review.
KEYWORDS*: Artificial intelligence, machine learning, smart wound dressing, wound assessment and wound healing.*

Received 10.02.2025 Revised 01.03.2025 Accepted 11.04.2025

How to cite this article:
Monika D K, Shilpa C· Role of Artificial Intelligence in Wound Healing. Adv. Biores., Vol 16 (3) May 2025: 231-236.

INTRODUCTION

A cut results from a break in the surface of the skin or from conditions like burns, psoriasis, eczema, and dystrophic epidermolysis bullosa. The cause of it is a disturbance of the norm anatomical structures and functioning [1-3]. Wounds are characterised based on the American Society of Anesthesiology score, which takes into account factors such the injury's origins, position, dimension, depth, design, exposure to the outside world, degree of gross contamination, healing duration and severity, and potential infection risk [1, 2,4–8]. Typical types include temporary versus ongoing, accessible versus shut down, pure versus contaminated, inner versus outside, shallow versus deeply, partial depth versus entire thickness, surgery versus painful, and stress against ulcers caused by diabetes.

a] Hemostasis: Immediate response to stop bleeding.
b] Inflammatory Phase: Redness, swelling, and pain as the body defends against infection.
c]Proliferative Phase: Tissue repair and collagen formation.
d] Remodeling Phase: Maturation of scar tissue over time.

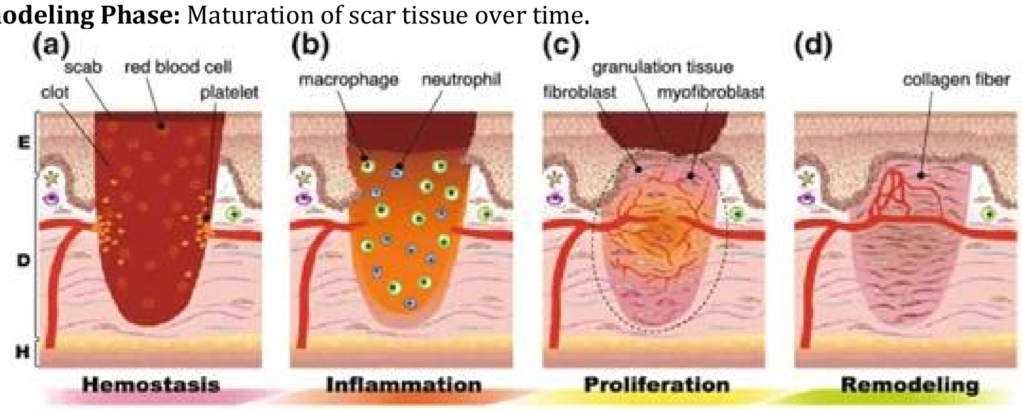

Fig 1: Stages of wound healing

Wound healing phases and the main cells required. The initial stage of wound healing is hemostasis, characterised by the creation of a primary fibrin matrix and a platelet pull to halt blood loss. The release of histamine by mast cells sets off the subsequent stage, inflammation, which starts with neutrophil flux to clear debris and stop infection. Monocytes are separated into tissue macrophages upon arrival; these macrophages do not include any leftover neutrophils or cell debris. During the proliferative phase, fibroblasts replace the initial fibrin clot with granulation tissue, keratinocytes cover the wound gap, and angiogenesis repairs blood vessels. Additionally required for this stage of recovery are macrophages and regulatory T cells, or Tregs. Fibroblasts eventually continue to alter the matrix that...After a while, blood vessels retreat, myofibroblasts force the wound to compress overall, and fibroblasts keep editing the matrix that has been deposited. [14,15, 16]. Image analysis allows for the reconstruction of the wound, including the periwound areas and its underlying components. Images can be used to evaluate the rate of wound healing. Computer scientists have been using artificial intelligence (AI) and computer algorithms to replicate and automate human thought processes since the 1950s [17]. ANNs [18,19] and fuzzy logic [20,21] are two of the primary machine learning methods used in artificial intelligence. Artificial intelligence (AI), which has been discovered to permeate most facets of modern technology and human existence, has been shown to be disseminated more quickly thanks to artificial neural network technology known as "deep learning" [19, 22].

ARTIFICIAL INTELLIGENCE IN WOUND ASSESSMENT

Clinical practice can greatly benefit from an efficient and successful evaluation of acute as well as long-term wounds. This can help wound care teams achieve better patient outcomes in terms of related to health quality of life, optimise treatment regimens, minimise workloads, and improve wound diagnosis. because of a shortage of skilled wound specialists in primary and remote medical environments, many patients with wounds may not possess access to professional wound care and current recommendations. The advancement of remote telemedicine technologies has made it possible to offer patients in remote areas—especially rustic ones—better diagnostic advice [23]. Given the increasing use in terms of artificial intelligence (AI) technology and portable gadgets like cellphones, it's currently appropriate to grow intelligent and remote evaluation, prediction systems for wound care. Improved accuracy, reduced workload and cost, standardised identification and administration, and better patient care are just a few of the numerous reasons that a clever system has the potential to be extremely advantageous to treat wounds [24].

WOUND ASSESSMENT FRAMEWORK

The computerised in segmentation, a deep learning model is utilised to identify the dead tissue, granulation tissue, and the wound region, and epithelialization area, and the automatic colour calibration, that is normalises the colour of a a picture of the wound for more precise examination of images, make up the framework for wound assessment. We utilised a multi-task deep learning model with two output branches: one for the segmentation of the wound area and the other for the segmentation of the wound tissue since there are two types of wound tissue and the wound area is the part of the body where the skin is exposed to injury.

The colour and measurement calibration chart can be used to convert the model to the actual metric scale. After then, this can be used to track how the treatment is progressing.[25]

WOUND DETECTION

The process consists of three primary parts: An electronic system that defines the wound's perimeter by choosing the interest region; an automated system that measures the area with the help of a system; an external calibrator that uses a convolutional network with training to categorise the tissues of the wound. Clinicgram®, a smartphone application, was used to apply these techniques to clinical settings. This mechanism's primary objective is to find the wound's edge in the picture. It utilises the resemblance in between neighbouring pixels. As soon as taking a picture of the injury using Using a smartphone, the user scribbles something inside the wound's position to assist the system in determining the woundFig. 3. Once the system has after determining the wound's outline, a mask is put on to separate the area of interest from the surrounding area and the intact skin. After experimenting with various methods (including Felzenszwalb [26], mean shift, and Quick shift [27]), The framework employs a superpixel technique [28,29] and a k-means technique [30] to ascertain the Region of Interest (ROI) boundaries and the shape of the wound. Using an automatic procedure, the superpixel approach splits a divided the image into sections that share comparable features or have consistent interpretations. The unsupervised classification algorithm k-means, on the other hand, clusters objects according to their attributes by minimising the total of the separations between every item and its cluster or grouping centroid, which is normally determined by its quadratic distance.

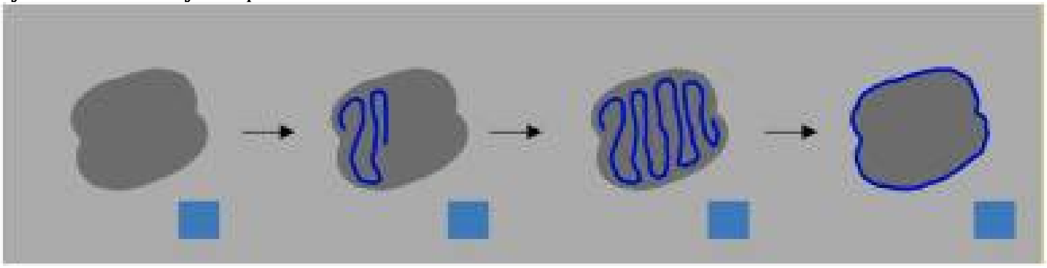

Fig 2 Two examples of how the system can identify a wound are as follows: first, take a test image; then, using that image as a guide, Lastly, get the wound mask after drawing inside the area of interest.

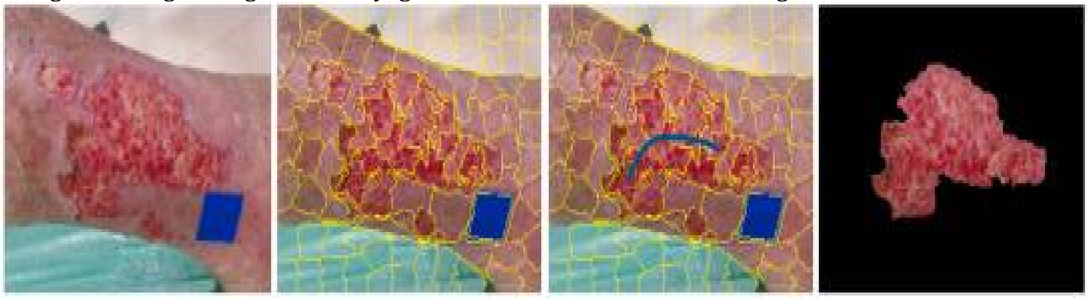

Fig 3 An illustration of a decoded region of interest, a scraw image, an image with superpixel segmentation, and an original image

AREA CALCULATION

You'll need a marker or calibrator., and the wound area is computed using the return on investment from the earlier stage. The marker in this instance is a blue square to set it apart from the background. This square marker's physical dimensions are always 2 cm on each side; therefore, we can compute the actual wound area by interpolating the marker's size from the image.

TISSUE CLASSIFICATION

One of the most crucial aspects of effectively identifying the tissue in wound imaging is accurately segmenting the tissue sections found in the sample. Erroneous boundaries, uneven forms, and very diverse hues can all be seen in complex wounds [31]. It was suggested that a convolutional network be used to build a system that categorises the many kinds of wounds. As a result, a dataset of wounds (n=726) was used to train multiple models.

GADGETS AND SOFTWARE-BASED COMPUTER TECHNIQUES

The conventional techniques include digital planimetry from images, transparent acetate planimetry, and graduated ruler measurement. Because square ruler measuring is rapid, easy, and doesn't require any specific training, it is frequently employed in normal clinical practice. Its accuracy is restricted, though, particularly when measuring wounds with irregular shapes. Furthermore, precision usually decline with more severe wounds, and this method typically overestimates the real wound size. [32, 33].

Applications and software for wound planimetry that are sold commercially include [32,34].

- The Silhouette Mobile, a Class I (FDA) gadget, is connected to a computerised personal assistant through its laser beam scanning head and camera. The surface topography of the wound is described by the laser line curves formed by the laser beams. These line curves are computed by the personal digital assistant to produce a three-dimensional representation of the wound surface. Using a stylus, the doctor draws the image's wound margin to compute the wound area. [32].
- Developed in 2013, AreaMe® is a software application for mobile devices that tracks the location of a wound using a 1 x 1 cm grid. This is not a certified medical device. The borders of the injury have to be physically delineated on a translucent sheet that was positioned above the injury earlier. The programme also creates a graph showing the evolution of the wound area over time and uploads the information to a medical database.
- This need was addressed by the development of the NDKare® application, which our study assesses for accuracy and usefulness in the measurement of DFU wound size. It was evaluated how accurate the NDKare mobile application is at measuring both two- and three-dimensional (3D) wounds.

- ImitoMeasure®: Digital wound measurement enables accurate wound measurement without the use of a scale.
- WoundVue®: this technology not only objectively classifies the different tissue types present in a wound, but it can also measure the volume and surface area of a wound.
- Planimetor®: Two calibration markers that are one dimensional were positioned beneath and above the incision's contour to determine the planimetric area.
- The models Pictzar CDM and PRO®. Using a ruler next to the lesion, this software takes digital photos of the skin lesion to measure it. They don't need to know how far the subject is from the camera lens, but they do need a ruler in the picture.
- Wound Matrix®. The surface of skin lesions is measured by this telemedicine programme. It is mostly meant for businesses and organisations.
- WoundWiseIQ. The purpose of this software is to quantify skin lesions. It can only be used using ions as the operating system.
- A Class II device is the Visitrak (FDA)gadget that uses a translucent tracing sheet with two layers with a previously created wound out-line to calculate the wound area. Following the injury has been tracked down and positioned on the Visitrak device, the clean layer and contaminated layer are separated. In order to assess the wound area, the physicians redraw the wound contour using the Visitrak pen [32]. Compared to the manual planimetry method using transparent acetate, Visitrak offers higher measuring precision. However, because Visitrak needs to come into contact with the injury surface, there is a higher possibility of infection, pain, and harm to the incision.

MACHINE LEARNING

Machine learning employs the available data to teach an algorithm or function, negating the need for hand-crafted rules. It is feasible to use both supervised and unsupervised machine learning techniques. With the help of labels and input data, supervised machine learning techniques may automatically map input data to the correct output. Numerous well-known supervised algorithms consist of neural networks (NN), decision trees (DT), logistic regression (LR), k-nearest neighbour; (KNN), Bayesian network (BN), random forest (RF), radial basis function networks (RBF), discriminant analysis (DA), support vector machine (SVM), Naïve Bayes (NB), single- and multi-layered perceptrons (MLP), [35, 36]

PROFOUND UNDERSTANDING

Deep education is a subfield of machine intelligence that takes its cues from the human brain. Rather than requiring human-designed rules, deep learning supervised learning) or unsupervised learning) that groups input into distinct labels based on massive amounts of data [37]. explored various well-liked methods, such as stacked (denoising) autoencoders, Convolutional neural networks, deep belief networks, and deep boltzmann machines are examined in a deep learning algorithms survey for computer vision. Additionally, a number of well-known deep learning techniques for medical image analysis have been discussed, including variationsal auto-encoders and restricted boltzmann machines and deep belief networks, generative adversarial networks, GoogleNet, AlexNet, VGG 19, FCNN, ResNet, RNNs, LeNet, and auto-encoders and stacked auto-encoders [38].

SMART WOUND DRESSING

Unlike the conventional ways of assessing wounds, which involve making physical touch with a measuring tool like a plastic film or ruler, smartphone-based approaches can, in their most basic form, be non-contact and rely on digital image processing [39, 40]. Without the need for additional equipment or specialised training, the superior quality of the image's technologies found on modern Mobile phones can greatly improve the accuracy and dependability of wound measures [41, 42, 43]. The development of mobile applications and new advancements in electronics have stoked expectations for the creation of sophisticated smart instruments that can prevent infection and impede the healing process in order to treat chronic wounds., while also providing adequate diagnostic data. These intelligent technologies have the capacity to accurately sense, report, and act upon an instruction as needed. In this sense, sensors constitute the first essential step. Sensors can reduce the amount of time needed to make decisions about wound care without requiring frequent clinician visits or dressing changes by offering a clear map based on the most important criteria of the wound status. Ultimately, these developments result in lower medical expenses and shorter hospital stays [44, 45]. The important factors are the pressure, pH, wound oxygenation level, and uric acid content [fig 4].

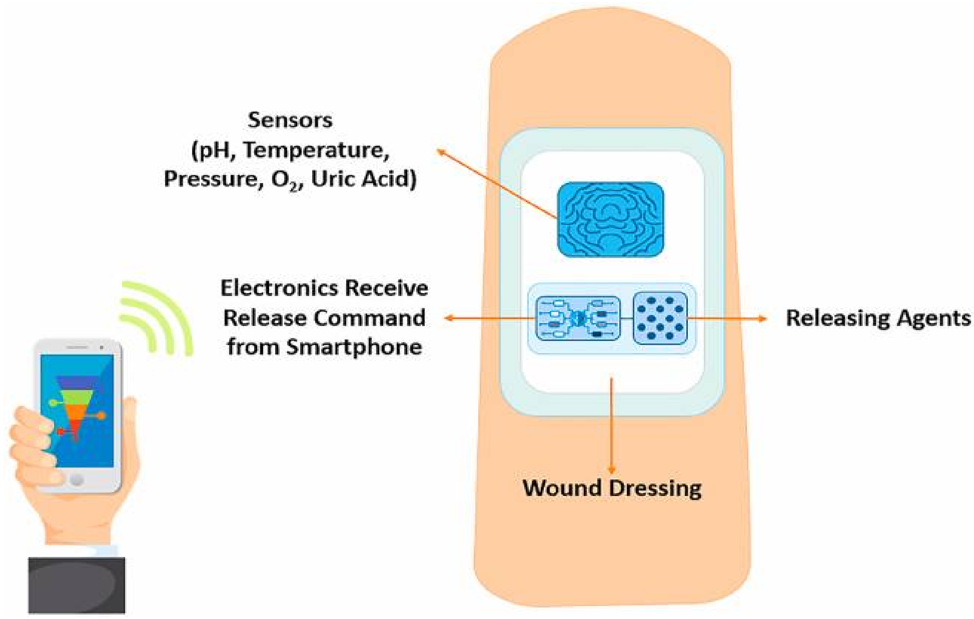

Fig 4 Dressing that is smartphone-based and has the capacity to administer medication and monitor wounds

CONCLUSION

In conclusion, by offering objective assessment, customised treatment plans, and predictive analytics, artificial intelligence is a useful tool in the advancement of wound healing. Even though there are a number of obstacles to overcome before AI can fully realise its potential to improve patient outcomes and optimise the administration of wound care, research efforts are encouraging. Sustained cooperation among physicians, scientists, and tech creators is important in order to fully use artificial intelligence's advantages and convert them into significant advancements in the treatment of wound healing.

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