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AI-enabled wound assessment in surgical practice: Current capabilities and future directions

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Abstract

Background: Chronic wounds, diabetic foot ulcers, pressure ulcers, and venous leg ulcers remain a persistent clinical challenge. Assessment depends heavily on subjective judgment, which drives inter-observer variability and inconsistent management. Artificial intelligence (AI) is addressing this gap by generating objective, reproducible, data-driven evaluations that complement clinician expertise.

Aim: This review synthesises current AI applications in chronic wound assessment and outlines practical pathways for wider clinical integration.

Current State: Smartphone-based imaging platforms enable standardised wound photography with automatic area and volume measurement. Deep learning models classify granulation, slough, and necrotic tissue at accuracy levels comparable to experienced clinicians. Sensor-based systems detect early infection signals through pH shifts, temperature gradients, and exudate composition. Predictive models estimate healing trajectories from patient demographics and comorbidities. AI-assisted decision support, linked to telemedicine infrastructure, extends specialist oversight to remote and resource-limited settings.

Future Directions: Biosensor-embedded dressings will enable continuous real-time monitoring of wound pH, oxygenation, temperature, and bacterial load, triggering early alerts before clinical deterioration is visible. Three-dimensional and four-dimensional imaging combined with patient-specific genomic and microbiome data will support personalised prognosis models and digital twin simulations for non-invasive treatment planning. AI-guided robotic debridement, integrated tele-wound clinics, and risk-stratification models for preventing chronic wound development represent further near-horizon applications.

Conclusion: AI has the potential to shift wound care from periodic, subjective review to continuous, standardised monitoring. Realising this potential requires prospective clinical validation, interoperability with existing health infrastructure, and coordinated input from clinicians, engineers, and regulators.

Keywords: Artificial Intelligence; Wound Assessment; Deep Learning; Chronic Wounds; Digital Twin; Biosensor; Wound Care; Surgical Practice

1. Introduction

Chronic wounds affect an estimated 2–3% of the population in high-income countries, with prevalence rising sharply among older adults and patients with diabetes, peripheral vascular disease, or prolonged immobility [1]. Diabetic foot

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ulcers alone account for a substantial proportion of lower-limb amputations and carry mortality rates that rival many cancers [2]. Despite these figures, wound assessment in most clinical settings still relies on subjective measurement with a ruler, visual tissue classification, and documentation that varies from one clinician to the next [3].

This variability is not a failure of clinical skill; it is a structural problem. Wounds change continuously, patients are reviewed intermittently, and accurate repeated measurement of an irregular three-dimensional surface is genuinely difficult without calibrated tools. The result is delayed recognition of deterioration, inconsistent documentation for research and audit, and inefficient use of specialist time in referral pathways [4].

Artificial intelligence (AI), particularly deep learning applied to imaging, offers a practical route out of this impasse. AI systems do not tire, do not experience inter-rater drift, and can be embedded directly into the devices clinicians already carry. Over the past decade, a growing body of work has shown that convolutional neural networks (CNNs) can measure wound dimensions from standard photographs, classify tissue types with clinician-comparable accuracy, and predict healing trajectories from routinely collected data [5,6]. The question has shifted from whether AI can perform these tasks to how its outputs can be made reliable, interpretable, and genuinely useful inside real clinical workflows [7].

This review describes the current state of AI in wound assessment, what systems exist, what evidence supports them, and what limitations remain and then outlines the near-future technologies that are likely to reshape wound care over the next decade. It is directed at surgical and clinical teams who want a grounded account of what AI can and cannot do, rather than a promotional survey of vendor claims.

2. Current AI Capabilities in Wound Assessment

2.1. Automated Wound Measurement and Documentation

Accurate wound measurement is deceptively hard. Clinician measurements of the same wound using a standard ruler vary by 20–40% in published reproducibility studies [3]. Smartphone-based platforms address this directly: a photograph taken with a calibrated marker allows automatic segmentation of wound edges, extraction of surface area and perimeter, and three-dimensional depth estimation when stereophotogrammetry or structured light is available [8].

Several commercial systems have been validated against manual measurement, consistently showing narrower limits of agreement than inter-rater manual measurement [6]. The clinical benefit extends beyond measurement precision: automatic documentation removes a step from nursing workflow, creates a longitudinal photographic record, and generates data that can feed downstream predictive models. Integration with electronic medical records (EMR) is now technically straightforward and has been demonstrated in burn care settings [9].

2.2. Tissue Classification

Tissue composition, the proportion of granulation, slough, necrosis, and epithelialising tissue, is the primary indicator of wound trajectory. CNNs trained on annotated wound images now classify these tissue types at sensitivity and specificity values reported in the range of 85–95%, broadly comparable to experienced wound care nurses and surgeons [5,10].

The clinical relevance of accurate tissue classification is direct: a wound assessed as 60% slough that is 80% slough carries a materially different prognosis and calls for a different debridement strategy. Automated classification reduces the cognitive load on the assessing clinician and, crucially, allows trend tracking across multiple visits that is impractical without objective measurement [11]. Multimodal approaches combining visible-light imaging with thermal or near-infrared imaging improve classification accuracy and add the ability to detect subsurface changes not visible to the naked eye [12]. These platforms are moving from research settings into clinical pilots, particularly in diabetic foot services.

2.3. Infection Detection and Early Warning

Wound infection is often detectable before frank clinical signs appear, through biochemical signals in wound exudate, rising pH, falling oxygen tension, and production of specific bacterial metabolites [13]. Wearable and patch-type biosensors incorporating electrochemical detection arrays can now monitor these markers continuously and relay data wirelessly [14]. When combined with AI pattern recognition applied to the sensor time series, these systems can distinguish colonisation from early invasive infection with area-under-curve values exceeding 0.85 in preliminary clinical studies [13].

Visual infection detection using standard imaging has also advanced. CNN-based classifiers trained to identify periwound erythema, oedema, and exudate colour have shown diagnostic accuracy approaching that of tissue culture, though current evidence remains limited to single-centre datasets requiring external validation [6].

2.4. Healing Prediction and Decision Support

Risk stratification is an area where AI meaningfully outperforms intuition. Machine learning models trained on wound characteristics, patient demographics, comorbidities, and treatment history can predict non-healing at 4, 8, and 12 weeks with accuracy substantially above baseline clinician judgment [1,15]. Identifying the 20% of wounds most likely to fail conservative treatment early enough to change management represents a genuine advance in resource allocation.

Decision support platforms embedding these models alongside dressing recommendation algorithms and referral triggers are commercially available in several health systems. Their real-world impact depends heavily on workflow integration systems that require a separate log-in or that present recommendations in a format clinicians cannot act on quickly tend to be bypassed [7]. The most credible implementations are those embedded directly into the EMR and visible at the point of care without additional steps [9].

2.5. Telemedicine and Remote Wound Monitoring

The combination of standardised imaging, AI measurement, and digital documentation creates the infrastructure for remote wound monitoring without specialist travel. Patients or community nurses photograph wounds using validated applications; the system measures, classifies, and flags concerning changes; and a specialist reviews the output asynchronously or synchronously as urgency dictates [4].

Evidence from pilot programmes in diabetic foot and leg ulcer care suggests that AI-supported remote monitoring reduces unnecessary outpatient visits, detects deterioration earlier than scheduled reviews, and is acceptable to patients across a wide age range [4]. Extending this capability to resource-limited settings, rural clinics, nursing homes, and low- and middle-income countries is a logical and important next step.

Table 1 Summary of Current AI Capabilities in Wound Care

Application Domain	AI Approach	Performance Metric	Evidence Level
Wound measurement	CNN segmentation + photogrammetry	Comparable to an expert ruler (±5–10%)	Prospective pilot studies
Tissue classification	CNN image classification	Sensitivity/specificity 85–95%	Retrospective + prospective
Infection detection	Biosensor + time-series AI	AUC >0.85 (early infection)	Early clinical pilots
Healing prediction	Machine learning on EHR data	Outperforms the clinician baseline	Retrospective cohorts
Remote monitoring	App-based imaging + AI triage	Reduced visits; earlier detection	Prospective pilots

3. Future directions

3.1. Smart Dressings and the Internet of Bodies

The next generation of wound dressings will contain embedded electrochemical sensors measuring pH, dissolved oxygen, temperature, and bacterial metabolite concentration in real time [13,14]. These systems, sometimes grouped under the term Internet of Bodies (IoB), transmit data continuously to a clinical platform where AI algorithms generate alerts when parameters cross thresholds predictive of infection or non-healing.

The practical advantage over periodic clinic measurement is substantial. A wound that shifts from pH 7.4 to pH 8.2 over 48 hours may be clinically indistinguishable at a routine review but represents a biologically significant change that precedes visible deterioration. Continuous capture of this signal, paired with AI trend detection, could trigger a same-day assessment rather than waiting for the next scheduled visit [14].

Closed-loop prototypes in which the dressing both detects and responds, releasing antimicrobials or growth factors when threshold parameters are met, are at early experimental stages. The regulatory and safety questions around active, autonomous dressings are substantial, but the concept is technically feasible and likely to reach trials within the decade.

3.2. Three-Dimensional and Four-Dimensional Wound Imaging

Current AI wound measurement relies predominantly on two-dimensional photographs. Three-dimensional (3D) imaging using structured light, laser scanning, or stereophotogrammetry captures volume and surface topology in a single acquisition, enabling more precise tracking of depth changes and undermined edges that 2D imaging misses [8].

Four-dimensional imaging adds the temporal dimension, modelling wound geometry as a dynamic structure rather than a static snapshot. Combined with AI-driven segmentation, 3D/4D systems could automatically quantify tissue regeneration layer by layer across visits, providing an objective healing rate rather than a subjective clinical impression [5,15].

Consumer-grade 3D scanning hardware integrated into smartphone attachments is now available at cost points realistic for clinical settings. The principal bottleneck is annotation of 3D training datasets, which remains labour-intensive. Crowdsourced annotation and synthetic data generation using generative AI models are being explored to accelerate this step.

3.3. Genomic and Microbiome-Informed AI Models

Wound healing trajectories are substantially shaped by host genetics and the wound microbiome. Variants in genes regulating inflammatory response, collagen synthesis, and vascular function contribute to individual differences in healing that demographic and clinical variables alone cannot explain [16].

The wound microbiome, the community of bacteria, fungi, and archaea colonising wound surfaces, has emerged as an important predictor of healing. A structural equation model integrating microbiome 16S rRNA sequencing with clinical metadata predicted healing outcomes in diabetic foot ulcers with approximately 94% accuracy, with the microbiome contributing the largest proportion of variance explained [16,17]. Integrating these data streams with AI imaging analysis represents a genuine advance in predictive capability, though the cost and processing time of routine sequencing currently limit clinical deployment.

Multimodal AI frameworks designed to fuse genomic, microbiome, imaging, and clinical data are conceptually well-developed [18,19]. The practical challenges standardising sequencing pipelines, managing data volumes, and ensuring interoperability across systems are engineering and governance problems as much as scientific ones.

3.4. Digital Twin Simulations for Personalised Wound Management

A digital twin, in its clinical application, is a continuously updated computational model of an individual patient that can simulate physiological states and test treatment options in silico before applying them in vivo [20,21]. In wound care, a patient-specific digital twin would integrate real-time biosensor data, imaging measurements, genomic profiles, and microbiome composition into a dynamic model of wound biology [22].

Such a model could simulate the expected response to dressing A versus dressing B, predict the impact of surgical debridement on wound volume and tissue composition, or identify the point at which a wound trajectory is diverging from the predicted healing path and intervention is required [20,23]. Digital twins have already been demonstrated in oncology and cardiology settings; their application to wound care is a natural extension that is actively being developed [24,25].

The computational requirements are substantial, but cloud-based infrastructure makes centralised processing accessible without edge-device constraints. The greater challenges are data integration and model validation. A digital twin is only clinically useful if its predictions are prospectively accurate in an independent population, which requires the kind of multi-site trial infrastructure that wound care research has historically lacked [21].

3.5. AI-Guided Robotic Debridement

Surgical debridement removal of necrotic and devitalised tissue is technically demanding, particularly in complex wounds near tendons, vessels, or bony prominences. AI-guided robotic systems that map wound anatomy from 3D imaging, identify safe debridement planes, and guide instrument movement represent a logical extension of surgical robotics into wound care [26].

These systems are not imminent in routine clinical use. The levels of tissue discrimination accuracy and haptic feedback required for safe autonomous debridement exceed what current platforms deliver. Collaborative rather than autonomous operation, the robot handling precise movements within safe zones identified by AI, under constant surgeon supervision, is the more realistic near-term model and the one that current regulatory frameworks can accommodate [7,26].

3.6. Integrated Tele-Wound Clinics

The logical integration of home biosensors, standardised imaging, AI analysis, and specialist review is the tele-wound clinic: a digital environment in which wound data from the patient's home flows into a clinical dashboard, is processed by AI, and is reviewed by a specialist without requiring physical attendance [4].

This model has direct implications for high-risk group patients with diabetic foot ulcers, those in nursing homes, or those in areas with limited specialist access, for whom transport to outpatient appointments is burdensome and delayed recognition of deterioration is costly. The technology components exist now; the barriers are organisational, regulatory, and financial rather than technical [4,14].

Table 2 Near-Future AI Innovations in Wound Care: Timeline and Readiness

Innovation	Key Enabling Technology	Expected Timeline	Primary Barrier
Smart biosensor dressings	IoB sensors + real-time AI analytics	3–5 years	Regulatory approval
3D/4D wound imaging	Structured light + AI segmentation	2–4 years	Training data annotation
Microbiome-informed AI	16S rRNA sequencing + multimodal fusion	5–7 years (routine)	Sequencing cost
Digital twin wound simulation	Multimodal AI + cloud computing	5–8 years	Prospective validation
AI-guided robotic debridement	3D mapping + surgical robotics	8–12 years	Safety and regulation
Integrated tele-wound clinic	Biosensor + imaging + AI dashboard	2–5 years	Organisational adoption

4. Barriers to Clinical Integration

Several well-characterised obstacles slow the translation of AI wound technologies from research to routine practice. Understanding them is as important as cataloguing the technologies themselves.

Data quality and diversity. Most wound AI models have been trained on datasets from single institutions, often photographed under controlled conditions and biased toward particular patient populations. Performance frequently degrades when these models are applied to photographs taken in community nursing, care homes, or emergency settings with variable lighting and patient positioning [5,27]. Federated learning approaches training models across distributed datasets without centralising patient data represent a practical path to broader and more representative training without the governance barriers of centralised data sharing.

Interpretability. Clinicians are, not unreasonably, reluctant to act on a recommendation they cannot interrogate. "Black box" deep learning models that produce a tissue classification without any indication of uncertainty or reasoning are less likely to be trusted and adopted than models that highlight the image regions driving their output [26,27]. Explainable AI (XAI) methods, attention maps, uncertainty quantification, LIME, and SHAP are now standard in academic wound AI research but are inconsistently implemented in commercial products.

Workflow integration. Systems that require a separate clinical step, a distinct application, a separate log-in, or a report that arrives in a different inbox are typically ignored once novelty wears off. AI tools that embed directly into the EMR, appear at the point of documentation rather than as a parallel process, and require no extra action from the clinician to generate output are the ones that change practice [9]. Regulatory and liability frameworks. Medical AI is increasingly subject to regulation as a medical device in most jurisdictions. Approval processes for AI systems that learn and update their models after deployment remain unresolved in several regulatory frameworks. The liability question of who is responsible when an AI recommendation contributes to a poor outcome is not yet settled in case law and creates conservatism among both providers and healthcare institutions [7].

5. Implications for Surgical Teams

Surgical teams carry primary responsibility for wound assessment in the postoperative period, in complex chronic wound management, and in the decision to re-operate or escalate. Several practical implications follow from the current state of AI in this domain.

Standardised wound documentation should be adopted now. The clinical and research benefits of consistent, objective wound measurement using currently available validated applications do not require waiting for AI sophistication to advance. Establishing a photographic documentation standard within a department creates data that will support AI model training and retrospective audit regardless of how AI tools evolve.

AI decision support should be understood as a second opinion, not a replacement opinion. The appropriate mental model for current AI tools is the same as for any clinical decision support: a prompt that may be correct, may be wrong, and requires integration with clinical context before action. AI tissue classification that disagrees with clinical assessment is worth investigating, not automatically overriding.

Surgeons should participate in AI validation, not merely consume its products. Published AI wound systems are often trained on datasets that under-represent surgical wounds, traumatic wounds, and wounds in the perioperative context. Surgical units that contribute annotated imaging to research consortia, or that participate in prospective validation studies, will produce systems better suited to their own practice.

Investment in digital infrastructure is a prerequisite, not a luxury. AI wound tools are software solutions that require compatible hardware (standardised imaging devices), network connectivity, EMR integration, and staff training. Departments that invest in this infrastructure for AI adoption also create the foundation for telemedicine, remote monitoring, and audit capability.

6. Conclusion

AI has moved beyond proof-of-concept in wound assessment. Validated tools for automated measurement, tissue classification, infection detection, healing prediction, and remote monitoring are in clinical use, and the evidence base supporting them continues to grow. The honest caveat is that much of the evidence is retrospective, single-centre, and generated under conditions that do not fully replicate busy clinical environments. The near-future technologies described in this review, such as smart biosensor dressings, 3D/4D imaging, microbiome-informed models, digital twins, and integrated tele-wound clinics, are not science fiction. Their component technologies exist; the work lies in integration, validation, and implementation. The timeline depends substantially on whether clinical and research communities invest in multi-site prospective evaluation and whether regulators develop frameworks that can keep pace with software that learns. What is already within reach is the replacement of interval, subjective wound assessment with continuous, objective monitoring linked to decision support tools. For high-risk patient groups, such as people with diabetic foot disease, pressure injuries, or complex surgical wounds that shift alone, would reduce delayed recognition of deterioration, improve consistency across clinical settings, and create the standardised datasets that better AI depends on. That is a realistic near-term goal, and it starts with adopting the tools that already work.

Compliance with ethical standards

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Disclosure of conflict of interest

All Authors confirm no conflict of interest.

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