Assessing the Efficacy of AI Models in Medical Imaging Analysis for the Early Identification of Diabetic Foot Ulcers and Gangrene: A Review

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ABSTRACT

Artificial intelligence (AI) possesses the ability to transform diabetic foot care through enhancing the early identification, categorization, and management of diabetic foot ulcers and gangrene. Incorporation of multimodal sensors, privacy-preserving federated learning, and hybrid convolutional neural network–support vector machine frameworks are some of the AI-driven approaches synthesized in this narrative review. Improving diagnostic accuracy, real-time assessment of risks, and potentially scalable, cost-effective implementation within both urban and rural areas are all included in the clinical potential of AI technology, which the literature review highlighted. Still, there are numerous obstacles to overcome—including a lack of data, inconsistent annotations, outdated technology, biased algorithms—and the need for algorithms that are both explainable and ethically acceptable. In order to cross the gap between breakthrough technology and real-world clinical significance, collaborative attempts that involve standard protocols, compliance with regulations, health care provider commitment, and multidisciplinary teamwork are needed. By addressing these issues and promoting ethical, inclusive, and transparent AI applications, the field has the opportunity to advance in the direction of fair and reliable diabetic foot care, subsequently reducing morbidity and improving patient outcomes on a global basis.

Keywords: Diabetic foot ulcers, Gangrene detection, Convolutional neural networks, Federated learning, Explainable AI

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Introduction

Background and Epidemiology of Diabetes and Its Complications

Diabetes is a chronic illness defined by persistently high blood glucose levels, which adversely affect the body.[1] This is a severe worldwide problem that affects over 500 million people, mainly those with type 2 diabetes.[2,3] Prolonged elevated blood sugar levels can result in damage to blood vessels and nerves, potentially causing severe complications such as visual impairment, renal dysfunction, and cardiovascular disease.[4]

Major, expensive consequences of diabetes mellitus that greatly raise global morbidity, mortality, and health care stress are diabetic foot ulcers (DFUs).[5] DFUs arise due to a complex interplay of peripheral neuropathy, peripheral arterial disease, and repetitive trauma or pressure, often exacerbated by poor glycemic control and delayed wound healing.[5,6] Untreated foot ulcers can lead to infection, progress to gangrene, and potentially amputation of the foot or leg.[7] According to the World Health Organization, patients with Diabetes Mellitus (DM) are ten times more likely to need lower-limb amputations caused by DFUs than those without DM.[8]

Diabetes represents some harsh realities in terms of foot health. Studies indicate that almost one in three people with diabetes could eventually develop a foot ulcer. Every year, over 2% of Western patients develop these harms.[9] These ulcers can become serious problems. Between 14 and 24% of cases lead to amputations because the infection or tissue damage gets too severe.[6] Within 5 years, 30–70% of patients do not survive, especially if they have had an amputation. And even if someone heals, the problem often comes back—up to 65% of people experience ulcer recurrence within 5 years.[5]

Some people struggle greatly from DFUs and associated complications. Men, as well as people with type 2 diabetes and persons from lower-income or minority backgrounds, have higher incidences and amputation rates.[9] It becomes even worse if they are already dealing with heart or kidney problems on top of everything else. When other health issues, like heart or kidney problems, are present, the risk of adverse outcomes further increases.[5] Preventing and early identifying DFUs is difficult since their pathophysiology combines sensory, motor, and autonomic neuropathy; vascular insufficiency; foot deformities; and compromised immune response.[5,6] Often requiring quick action, gangrene, a severe manifestation marked by tissue death from infection and/or ischemia, is linked with an especially adverse prognosis.[10]

Significance of DFUs and Gangrene

Among the most severe and expensive consequences associated with diabetes mellitus are DFUs and gangrene. DFUs, which are causing 80% of amputations of the lower extremity in diabetic patients, impact about 18.6 million individuals globally annually. Deficient physical performance, deteriorated quality of life, and raised health care utilization have all been linked to the lifetime risk of having a foot ulcer in diabetes, and that has been reported to be 19–34%. Untreated DFUs may give rise to infection, gangrene, and limb loss; 15–24%[11] of cases end in amputation; the 5-year death rate after a significant amputation is over 70%.[5,12] Peripheral neuropathy, peripheral arterial disease, poor glucose control, co-morbidities such as renal or cardiovascular diseases, and previous experiences of ulceration or amputation are all factors that raise the possibility of this health issue.[13] Managing DFUs in the USA costs around \$9–13 billion a year.[12] Early diagnosis and multidisciplinary treatments are extremely important as they greatly reduce the risk of loss of limb and mortality.[5,12,13]

Clinical Challenges in Diagnosis

Inter-observer variation limits conventional evaluation techniques—based on observation, manual palpation, and subjective clinical judgment—and can miss early, subclinical alterations, particularly in areas with limited resources in which robust imaging techniques such as MRI (Magnetic Resonance Imaging) or CT (Computed Tomography) imaging have not become readily accessible.[14,15] Diagnosis and treatment delays are worsened by basic health care institutions' lack of expertise in wound evaluation and the dearth of established protocols.[16] In addition, due to overlapping visual characteristics and slight disparities in color, differentiating distinctive ulcer kinds—such as dry, wet, and gas gangrene—is particularly challenging. This points out the need for unbiased robotic systems capable of detecting preulcerative signs such as temperature imbalance (>2.2°C), irregular plantar pressure dispersion, and restricted erythema that have high sensitivity and specificity.[17]

Given these challenges, artificial intelligence (AI) offers scalable, cost-effective solutions for early diagnosis and management of diabetic foot complications. This review highlights recent advances and outstanding challenges, and proposes priorities for future ethical and effective clinical adoption. The main differences between traditional and AI-based evaluation approaches are summarized (Figure 1).

Methods

Review Design

This narrative review covered the clinical and technological applications of AI in medical imaging to identify gangrene and DFUs. Recent advances in AI algorithms—especially deep learning models and hybrid frameworks—and their clinical relevance, performance, limitations, and future prospects are emphasized (Figure 2).

This diagram illustrates the sequential stages in the literature review method, including searching the literature, identifying related studies, applying inclusion and exclusion standards, evaluating selected studies, comparing them to the gold standard, and identifying limitations.

Method of Searching Literature

A comprehensive and flexible search approach helped to capture the rapidly evolving environment of AI-driven DFU and gangrene diagnosis. PubMed/MEDLINE, Scopus, Google Scholar, Web of Science, Embase, IEEE Xplore, Science Direct, and Frontiers in Endocrinology[18] were searched for literature published between 2014 and 2025.[19] Search keywords were selected based on key concepts related to the topic. They included combinations of the following keywords: "diabetic foot ulcer," "gangrene," "artificial intelligence," "machine learning," "deep learning," "medical imaging," "convolutional neural networks," and "early detection," applied in various combinations.[20,21]

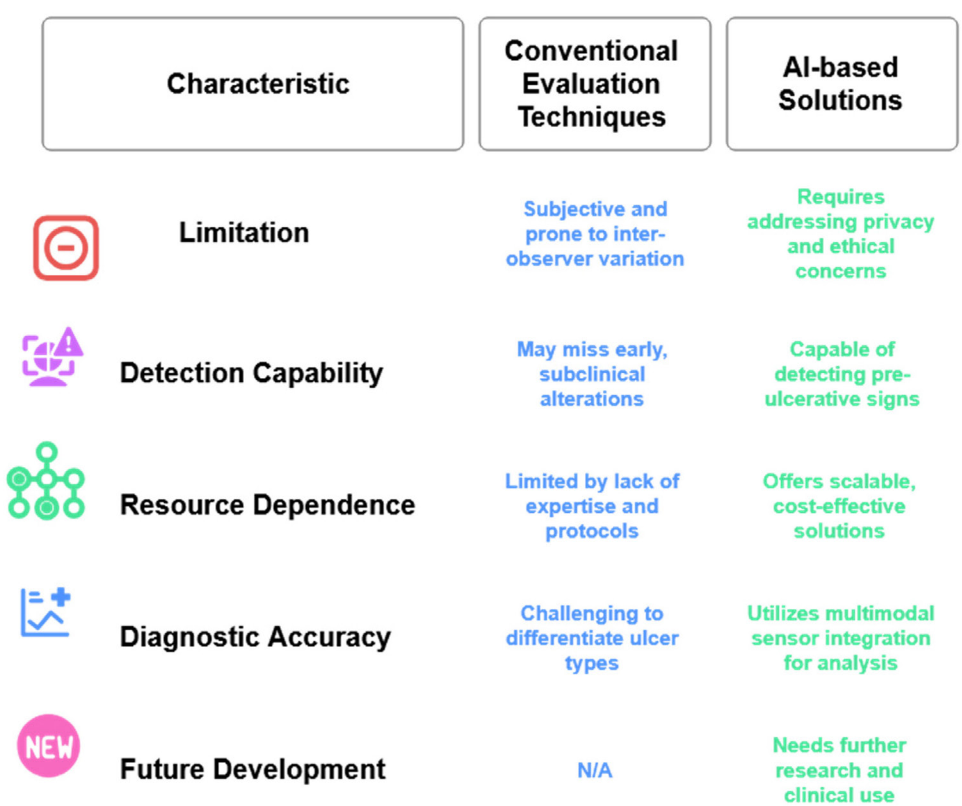

Fig 1 | Comparison of conventional evaluation techniques and AI-based solutions for diabetic foot issues

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Inclusion and Exclusion Criteria

Studies were chosen depending on the following criteria:

- Using medical imaging techniques, including Red-Green-Blue (RGB), infrared, or multimodal imaging, apply AI or ML (Machine Learning) to find, categorize, segment, or forecast DFU or gangrene.[18,19]
- Using sample sizes exceeding 100 patients or benchmark datasets such as DFUC-2021 (15,683 annotated images) for clinical validation.[20]
- Results compared to gold-standard diagnostics (e.g., Wagner scale) and inclusion of clinically important biomarkers.[21,22]
- Published in English-language studies from 2014 to 2025.

Studies were excluded if they were

- Non-English publications.
- Editorials, letters, case reports, or studies without methodological detail.
- Research not involving image-based AI analysis.

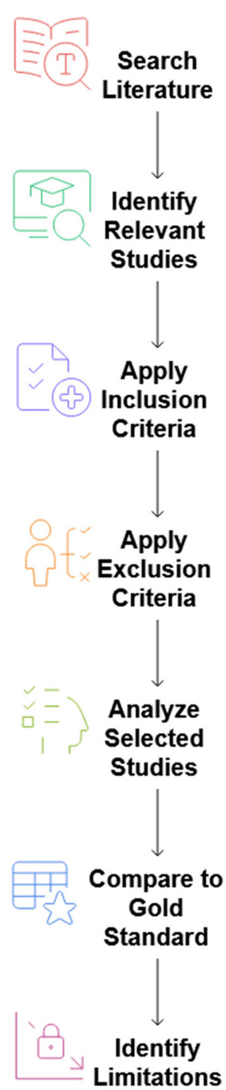

Fig 2 | Workflow of literature review and study selection process

Assessment of Methodological Quality

Owing to the narrative approach, no formal risk-of-bias tool or systematic quality grading was applied. Performance metrics (e.g., accuracy, sensitivity) are reported as published, but many studies lacked confidence intervals or detailed dataset characteristics, which is noted as a limitation. External validation and multisite evidence were rare in the included literature; these gaps are discussed in the synthesis and recommendations.

As this is a narrative review rather than a systematic review, formal study selection tools such as PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) were not applied. However, a summary workflow of the literature review process is provided in Figure 2.

Results and Discussion

AI's Impact on Diabetic Foot Care

AI is transforming diabetic foot care by enabling early detection, forecasting, and personalized therapy through advanced analysis of medical images such as RGB, infrared thermography, and multispectral data. Deep learning models—including convolutional neural networks (CNNs), Siamese Neural Networks (SNNs), and hybrid frameworks like convolutional neural network–support vector machine (CNN-SVM)—have demonstrated high diagnostic accuracy, achieving up to 98.76% in ulcer localization and 100% in gas gangrene classification.[21,23,24]

These technologies help doctors find early indicators of DFUs and gangrene, such as temperature imbalances of more than 2.2°C and irregular plantar foot pressure distributions.[22,25] By visually emphasizing key areas in medical imaging, explainable AI (XAI) tools like Grad-CAM heatmaps optimize diagnostic transparency and clinician trust, accordingly facilitating informed decision-making in practice in medicine.[23,26]

Applications of AI in DFU Detection

AI is quite important in speeding up diagnostic processes, enabling quicker and more accurate diagnoses of medical disorders. AI can help in the early identification of patients with life-threatening conditions and quickly notify doctors so the patients can get fast attention. The diagnosis of DFU is somewhat difficult for doctors, often involving multiple costly and time-consuming clinical examinations, which makes it challenging for health care providers to supply quick and dependable assessments. Deep learning, machine learning, and computer vision technologies have offered several ways to help doctors make more dependable and quicker diagnostic judgments in the era of data flood. Recent studies have focused more on the automatic identification of DFU.

Sensor Applications and Early Screening Technologies

AI-driven sensors provide early DFU recognition by applying presymptomatic alterations to recognize objects. Wearable pressure sensor platforms such as the DiaSense Project reach >90% predictive accuracy in real-world studies, highlighting the translational potential of AI-powered gait analysis for early DFU risk stratification.[27] Classified by CNNs like ResNet50 with 95% accuracy, thermal imaging detects temperature asymmetries (greater than 2.2°C) between foot areas.

With up to 89% sensitivity, infrared thermography is especially useful for preulcerative identification, spotting temperature anomalies (>2.2°C) between contralateral foot areas—a sign of inflammation or ischemia.[28] RGB imaging offers a vital structural and vascular background, therefore allowing the capture of details like erythema, necrosis, and callus formation, which are especially important for thorough DFU evaluation.[29,30]

Hybrid methods combining thermal and RGB imaging increase lesion localization by 18%.[31] With AI linking electrochemical sensor readings (neuropathy markers) and thermal anomalies for risk classification, emerging multimodal platforms combine pressure, temperature, and skin resistance data.[16] In a 200-patient research study, an artificial neural network (ANN) model trained on 19 variables predicted DFUs with 97% accuracy, surpassing decision trees (DT).[15]

The workflow for AI-driven DFU detection, integrating early symptom identification, plantar pressure tracking, and multimodal sensor data, is illustrated in Figure 3. This diagram illustrates the sequential steps in AI-based DFU detection, including early symptom identification, plantar pressure tracking, gait analysis, thermal imaging, integration of multimodal sensor data, and high-accuracy risk prediction.

Performance of AI Frameworks

Recent AI systems have enhanced diagnostic performance and applicability in gangrene and DFU imaging.[16]

Models based on ResNet50 and DenseNet121 achieve ~93% accuracy in DFU and gangrene diagnosis,[32] consistently ranking among the top performers across recent clinical studies. The introduction of generative adversarial network (GAN)-based augmentation (e.g., ResNet50-GAN hybrids) improves diagnostic accuracy and generalizability in diverse patient populations, underscoring the value of synthetic data in overcoming dataset limitations—a frequent barrier for DFU imaging studies.[18] GANS also allows prognostic models, which forecast the courses of ulcer development, supporting treatment alternatives.[32] CNN-SVM hybrid models outperform solo classifiers, reaching up to 85% accuracy for gangrene subtypes and exceptional sensitivity for gas gangrene.[24] However, their performance remains dependent on adequate data balance and clinical validation.

Subtype Classification Using Hybrid CNN-SVM Frameworks

Deep learning techniques, including CNNs and support vector machines (SVMs), and hybrid CNN-SVM frameworks, develop gangrene subtype categorization (wet, dry, gas).[24] This approach combines the feature extraction capabilities of CNNs with the robust classification performance of SVMs. It is like having one tool to spot the details and another to make sense of them. The idea is to achieve better accuracy in telling the subtypes apart. Basic aspects of the image have been collected using the first layer of a CNN. Also referred to as hidden layers, the intermediate layers generate several visual features like structure, contrast, brightness, and color. Finally, the CNN-derived features are sent into the SVMs to categorize the gangrene disease.[24] Researchers made an effort to categorize DFUs into multiple categories by combining SVM with VGG16, a type of CNN.[33] It was successful almost 87% of the time. Employing SVM in various ways, another team paired it with ResNet50 for analyzing both normal and infrared photos. With 89% sensitivity and 82% specificity,[34] the performance was quite effective at identifying early warning signs.

These hybrid AI platforms appear promising for medical diagnostics, despite their current lack of accuracy. According to studies, we still need additional

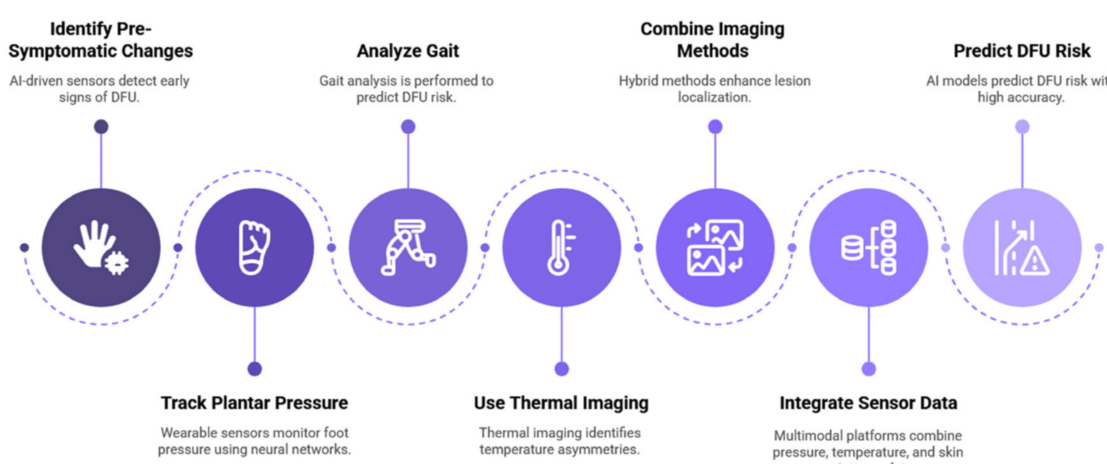

Fig 3 | Workflow of AI-driven DFU detection process

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Table 1 | Performance of AI-based technologies for gangrene detection and subtype classification

Technology	Application	Performance	References
CNN-SVM hybrid models	Gangrene subtype classifications (dry, wet, gas)	86.67% accuracy	33
ResNet50 + SVM	Multispectral image analysis for pregangrene detection	89% sensitivity, 82% specificity	34
Mobile AI with image enhancement	Multispectral image analysis for pregangrene detection	Improved visibility in low-quality images	35

data—bigger and more varied—to make sure these tools work well in real hospitals. Currently, these models remain at the proof-of-concept stage rather than being ready for routine clinical deployment. Following that, there is an issue of how to successfully set these measures in place in hectic clinics without causing delays. As summarized in Table 1, a direct comparison of AI-based methods for gangrene detection and subtype classification shows varying diagnostic performance across different approaches.

Siamese Neural Networks and XAI Frameworks

Ulcer localization performance of SNNs, as in the DFU_XAI framework, surpassed conventional models by reaching 98.76% accuracy, 99.3% precision, and 97.7% recall.[23] By bridging the "black box" gap and improving clinical confidence, integrated Grad-CAM heatmaps gave doctors interpretable visuals.[23] Significantly boosting lesion localization accuracy, multimodal fusion techniques like FusionSegNet combine thermal imaging with RGB data. In separating DFU images from non-DFU chronic wounds, FusionSegNet attained 95.78% accuracy, 94.27% sensitivity, and 96.88% specificity.[36] The DE-ResUNet dual-encoder model, which searches at thermal and RGB pictures separately, did better than the single U-Net (95% IoU) and got 97% IoU in ulcer segmentation.[18]

Despite the broad range of architectures and technical advances reported—including CNN-SVM hybrids, transformer-based models, and GAN-augmented networks—true progress in clinical translation is hindered by several recurring themes. While published accuracies are often high, most studies to date draw on institution-specific or internally validated datasets, limiting the generalizability of their findings. Algorithms that perform well in ideal conditions sometimes show diminished utility in settings where image quality, patient population, or care infrastructure differ from the training environment. Furthermore, the technical resource requirements of newer models (like transformers) remain a barrier to adoption in low-resource contexts. To realize sustained real-world benefit, future research must prioritize multisite validation, evaluate algorithm performance in representative populations, and proactively address equity and implementation challenges.

These advancements demonstrate that AI-driven frameworks can outperform traditional diagnostic methods and provide clinicians with reliable, interpretable tools for early intervention. Given these impressive technical results, the next major challenge is ensuring these models are interpretable and trusted by clinicians.

The Validation of Clinical Practice

Several AI models have undergone clinical validation, demonstrating strong correlation with gold-standard diagnostics such as Wagner grading and transcutaneous oxygen pressure ($TcPO_2$) measurements. By applying $TcPO_2$, ANNs anticipated DFU expansion with 97% precision, exceeding monofilament evaluation (68% sensitivity).[37] AI-powered mobile solutions, such as DFUCare, were able to detect ischemia with a 94.81% success rate utilizing multispectral smartphone photographs and pinpoint DFUs with an average precision (mAP) of 0.861 by automatically grading the photos from the phones.[38] The meta-analysis, which included 1,678 patients, found that the amputation rates were 36% lower (relative risk, RR = 0.64) and that each patient saved $4,158 compared to standard care.[39] Moreover, advanced AI models such as Mask2Former demonstrated high utility in wound assessment. Mask2Former measured gangrene extent (IOU: 77.14%) to guide debridement decisions, hence lowering unneeded revascularizations by 41%. Transformer models (e.g., ScoreDFUNet) segmented DFU images into ulcer, infection, and gangrene areas with 95.34% accuracy.[40]

XAI Frameworks

XAI addresses the "black box" limitations of AI, which is one of the major challenges in deploying AI in clinical settings, fostering clinician trust through transparent diagnostics. The DFU_XAI framework integrates SNNs with Grad-CAM heatmaps, achieving 98.76% accuracy in ulcer localization. While Grad-CAM indicates necrotic areas—e.g., erythema—SNNs evaluate embedded data of ulcerated tissues and tissue that is healthy, so diminishing mistaken positives by 25% linked to non-interpretable models.[23] Biswas et al.[41] addressed five DL (Deep Learning) models—Xception, DenseNet121, ResNet50, InceptionV3, and MobileNetV2—to generate a distinct DL framework. ResNet50 surpassed the other four models with unique outcomes of 98.75% accuracy and practical interpretability via heatmaps, enabling precise ulcer site identification and a key effective clinical intervention. These findings make it clear that explainability need not come at the expense of accuracy or performance. Beyond visual tools, emerging XAI strategies incorporate rule-based decision logic and attention mechanisms to further clarify model reasoning for end users. Such advances increasingly satisfy requirements from clinicians, patients, and health authorities, who now demand AI predictions to be accessible and auditable within the clinical workflow.[26,42]

As AI-guided diabetic foot care continues to evolve, robust and standardized explainable frameworks will be essential for safe, trustworthy adoption. Ongoing collaboration between AI developers, clinicians, and regulatory agencies will be critical to realizing the full clinical potential of these technologies.[43]

In summary, incorporating explainability into AI systems forms the foundation for ethical, accepted, and practical diabetic foot care, supporting better outcomes and greater confidence among both clinicians and patients.

Gangrene Detection

Gangrene is tissue damage secondary to infection, ischemia, or both. As a result of damage to the blood vessels throughout the body due to prolonged hyperglycemia, it is possible for blood circulation to be cut off. Blood carries oxygen and nutrients to the tissues around the body, and so without it, the tissues will eventually die. Though early detection is crucial, it is somewhat unusual.[44,45] Innovative imaging technologies are applied to diagnose the extent of tissue contribution and differentiate among several gangrene categories, comprising dry, moist, and gas gangrene. These techniques let doctors confirm the incidence of gangrene, categorize its subtype, and monitor rapid action to stop advanced tissue damage and systemic complications.[45]

The contribution of hybrid AI architectures to DFU and gangrene detection, and their impact on clinical robustness, is schematically represented in Figure 4.

Mobile Health, Telemedicine, and Real-Time Monitoring

Along with diagnosis, AI-driven mobile apps present 91.6% sensitivity and 88.6% specificity in DFU detection, thus allowing scalable telemedicine and enhancing access to care, especially in areas with limited resources.[46] Smart insoles and IoT-enabled wearable sensors additionally provide continual tracking of pressure, temperature, and gait patterns, thereby permitting immediate action and minimizing the amputation threat.[25] Recent improvements in telemedicine and mobile health technologies have made it possible to keep an eye on diabetic foot patients from a distance and all the time. More and more, AI-powered apps and smart devices are being used to find problems early, analyze risks, and take action quickly.

Mobile AI Solutions for Resource-Limited Settings

Using AI on phones to spot gangrene in places with limited resources is becoming a game changer. These mobile tools do not need fancy setups—they work with simple image tweaks like adjusting brightness and boosting contrast to make wounds easier to see, even in bad lighting.[35] That is huge for rural areas where medical help is not always around. Phones with basic cameras can now help monitor wounds from a distance, giving people a shot at catching gangrene early without needing to trek to a hospital. It is not perfect, but it is way better than nothing when options are slim.

Data Security, Privacy, and Federated Learning (FL)

Privacy-preserving technologies such as blockchain and FL further support secure, collaborative AI development across institutions, promoting equitable advancements in diabetic foot care.[43] The sensitive nature of medical imaging and patient health records used in AI model development raises significant concerns about data breaches, unauthorized access, and compliance with privacy regulations such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA). These challenges are particularly pronounced when data must be centralized from multiple hospitals or clinics, potentially exposing patient information to security risks. As these innovations become integrated into standard clinical practice, they are poised to lower diabetes-related morbidity, reduce health care costs, and improve quality of life for patients worldwide. Nevertheless, ongoing research is needed to address technical challenges such as communication efficiency, model convergence, and interoperability

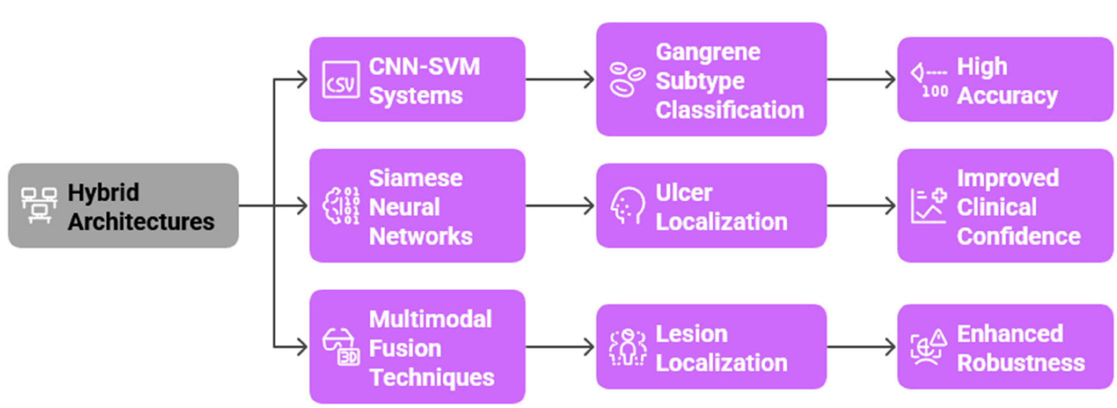

Fig 4 | Schematic overview of hybrid AI architectures for DFU and gangrene detection

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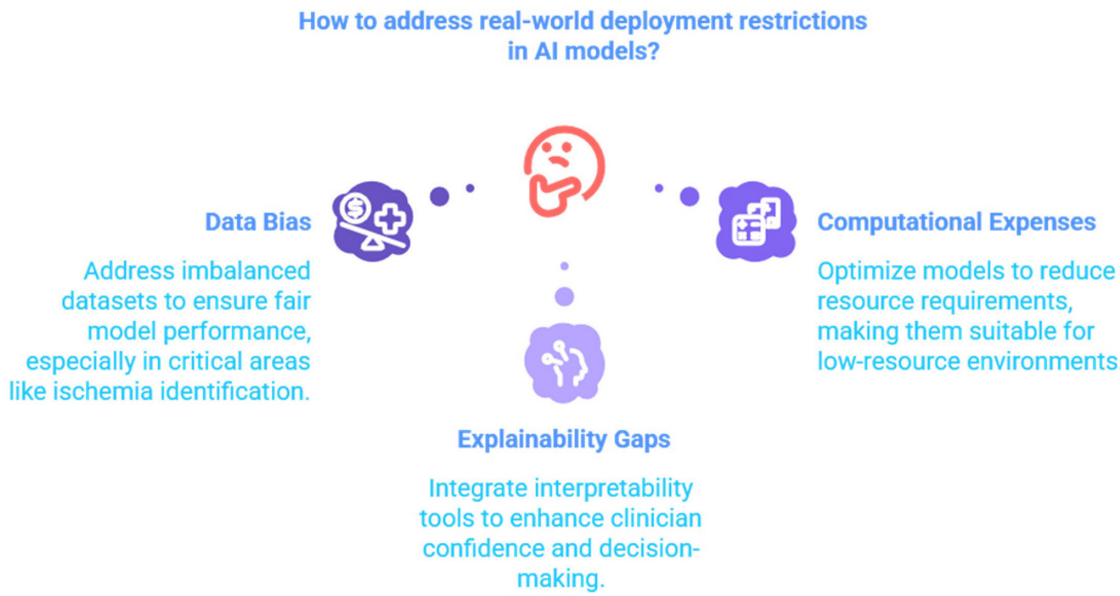

Fig 5 | Addressing real-world deployment restrictions in AI models for diabetic foot care

between different health information systems. The continued evolution and adoption of privacy-preserving AI frameworks will be essential for the trustworthy, scalable, and ethical deployment of AI in diabetic foot management.

Challenges of Using AI to Predict Gangrene and DFU

While encouraging outcomes in controlled circumstances, the true broad use of AI approaches for predicting gangrene and DFU is limited by an array of variables. Key barriers to real-world deployment of AI models, including data bias, computational expenses, and explainability gaps, along with strategies to address them, are summarized in Figure 5.

Data Bias and Imbalanced Datasets

Most frequently utilized datasets' skewed class distributions enforce an important limitation. The DFUC-2021 dataset, for instance, consisted of 1,703 infection images but only 152 ischemia samples and 372 combination ischemia/infection situations that underrepresented vital ulcer origins.[30] Particularly in ischemia recognition, which is essential for gangrene prediction, this prejudice could result in unjust model performance.

Cost of Computation and Resource Limitations

The deployment of advanced AI models is often constrained by high computational requirements. While ViTs have proven effective in high-resource research settings, their hardware demands often exceed what is available in community health clinics or mobile applications. Real-time systems such as YOLOv5 address this limitation and, according to recent field studies, maintain robust diagnostic accuracy with lower computational burden (mAP: 0.861). This suggests that resource-adapted models may offer greater immediate impact for population-scale DFU triage, even if their ultimate theoretical accuracy is slightly lower than that of transformer-based models.[20]

Gaps in Explainability

Explainability remains a significant barrier to clinical adoption of AI. Only 23% used SHAP (SHapley Additive exPlanations) or Grad-CAM as tools for explainability. Achieving an F1-score of 98.5% for ulcer localization, the DFU_XAI framework tackled this by producing Grad-CAM heatmaps using SNNs.[23] Likewise, the ScoreDFUNet design included Grad-CAM images to emphasize decision-making areas (e.g., periwound erythema), hence enhancing transparency and supporting clinician confidence.[42]

Evaluating AI Performance for Diabetic Detection

Robust performance criteria, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC), constitute the basis of the evaluation of AI algorithms in the scope of DFU and gangrene diagnosis. These criteria offer a statistical basis for assessing and comparing the therapeutic usefulness of different models.[18]

Accuracy and Classification Metrics in Diabetic Complication Detection

Recent Advances in AI-Powered DFU Detection and ClassificationRecent advances in AI have shown remarkable efficacy in addressing DFUs and their consequences. For instance, smartphone-based AI systems automatically identify DFUs with 91.6% sensitivity and 88.6% specificity, hence enabling real-time monitoring in resource-limited settings.[46] Comparative studies contrasting ANN and DT reveal ANN's superiority, with 97% accuracy in predicting DFU onset by combining medical history, foot images, and demographic data.[15]

The ScoreDFUNet model improves DFU evaluation to resemble expert dermatologist evaluations by accurately categorizing pictures into "ulcer," "infection," "normal," and "gangrene" regions with 95.34% resolution.[21] Complementing these developments, non-invasive sensor technologies, such as infrared thermography, identify preulcerative biomarkers (e.g., temperature anomalies >2.2°C) with 89% sensitivity, hence enabling timely preventive therapies.[22] Offering reasonably priced remote monitoring, AI-powered systems like DFUCare localize wounds (mean average accuracy: 0.861) and categorize ischemia with 94.81% certainty using computer vision and deep learning. These tools cut health care expenses by $4,158 per patient through telemedicine integration.[47] Advanced architectures like SNNs and other recent neural network topologies improve the accuracy of medical image confirmation and documentation techniques.[48] Heatmaps produced by the DFU_XAI framework, which incorporates SNNs with explainability approaches such as Grad-CAM, localize ulcer areas with a precision of 99.3%, an accuracy of 98.76%, and a recall of 97.7%; in the meantime, clinicians obtain clinically interpretable insights.[18,23] Principally for health care settings, this framework is compatible since it consumes less power and can catch tiny image structures.[49]

Valuation and Comparative Analysis of AI for Classifying Diabetic Gangrene

When it comes to using AI to categorize diabetic gangrene, the outcomes are very interesting. The system uses image analysis to sort gangrene into three types—dry, wet, and gas—and it gets it right with about 85% accuracy on average.[24] Gas gangrene is the easiest to spot because of obvious signs like subcutaneous emphysema, and the AI nails it every time.[24] But wet and dry gangrene? That is trickier. They can look a lot like infected ulcers or just have subtle color changes, so the AI does not always catch them. This also shows why having a good mix of data matters, especially for people with darker skin tones, since those cases do not always get enough attention in the datasets.[50]

Predicting the onset of DFUs, ANNs beat DT with a 97% accuracy.[15] By perfectly categorizing images into ulcer, infection, normal, and gangrene regions with 95.34% accuracy, the ScoreDFUNet model considerably increases DFU control, equivalent to skillful assessments.[23] In addition to these measures, thermal imaging can distinguish preulcerative temperature irregularity (>2.2°C) with a sensitivity of 89%, permitting rapid detection. By estimating fundus photography and optical coherence tomography, AI algorithms have reduced false positives in retinal screening for diabetic retinopathy, attaining an AUROC >0.95 and 97.9% specificity.[51]

By integrating Grad-CAM heatmaps and achieving 98.76% accuracy, explainability frameworks like DFU_XAI bridge these gaps and enhance clinicians' available information for management.[23] These days, mobile AI tech built into smartphones can cut diagnosis time spans in half while also providing scalable tools for usage in remote scenarios.[52] This could be a game changer for places where getting health care is a real struggle. Emerging paradigms like FL and edge computing optimizations are being tested out to keep patient info safe while still letting hospitals and clinics share what they need to. The use of AI for diabetes could be appreciated by all people, regardless of where they live, if they manage to figure it out.

Aspects Impacting Performance

Data Diversity: The performance of the model is directly affected by the quality, diversity, and capacity of the data.[53,54] The external validation performance trained and tested the models on all possible combinations of the datasets to identify the potential margin of generalization.[53,55] The Zivot protocol's systematic data collection across 269 patients, for example, made it possible to build a benchmark dataset (3,700 annotated pictures) that facilitates strong model training and cross-study comparisons.[56]

Validation Strategies: A validation procedure is for measuring whether or not the reported performance and reliability of AI models in health care is as it is supposed to be, or whether or not it is.[57] Internally validated models—those tested on data from the same source as the training set—often report higher accuracy, but this can be misleading due to potential overfitting and a lack of data heterogeneity, threatening institutional biases.[58] However,

Table 2 | Comparative performance of AI models in dfu and gangrene detection, classification, and segmentation

Model Type	Performance Metric	Data Modality	Accuracy/Other Metrics	References
ResNet50	Classification	Infrared thermography	93.1% accuracy	32,60
ResNet50-GAN	Ulcer detection	Multispectral	93.1% accuracy	32
CNN-SVM	Gangrene subtype classification	Multispectral	85% overall accuracy, 100% gas gangrene detection	24,61
DFU_XAI (SNN + Grad-CAM)	Ulcer localization	Medical imaging + explainability	98.76% accuracy, 99.3% precision, 97.7% recall	23,31
FusionSegNet	Lesion segmentation	Thermal + RGB	95.78% accuracy	36
DE-ResUNet	Ulcer segmentation	Thermal + RGB	97% Intersection over Union (IoU)	18
ANN	DFU prediction	Clinical history + foot images	97% accuracy	15
ScoreDFUNet	Wound categorization	Expert-annotated DFU images	95.34% accuracy	21

an improved measure of generalizability and stability is made available by external validation, which involves validating a model on a dataset that is not included in the internal validation approach. Despite the hopefulness and endorsement for external validation, the statistical power of the above types of investigations has not been checked.[59]

Comparative Analysis of AI Techniques

The comparative diagnostic accuracy, modality, and application domains of major AI models for DFU and gangrene are compiled in Table 2.

The results obtained indicate the importance of balancing accuracy with reasonable concerns regarding deployment, which includes computing expenses, explainability, and data diversity. This comparative analysis thus directly informs clinical integration strategies and the selection of future research priorities in AI for diabetic foot care.

Challenges and Limitations

Though AI shows great promise and accuracy in finding diabetes complications—including DFUs and gangrene—significant obstacles and constraints still exist throughout the data, technological, and clinical spectrum. The principal challenges facing AI implementation in diabetic foot care are summarized in Figure 6.

Issues with Data Scarcity, Fragmentation, and Annotation

The lack and fragmentation of vast, varied datasets are major obstacles for strong AI model creation. Most current datasets, such as the Zivot protocol (3,700 images from 269 patients) and Cairo University's trial (200 patients), are derived from single-center cohorts, lacking demographic and pathological diversity and underrepresenting populations in low-resource settings where diabetes prevalence is highest.[15] This creates spatial and clinical prejudices that compromise model generalizability. The annotation discrepancies exacerbate the problem further, given that expert labeling of DFUs and their subtypes is labor-intensive and prone to inter-annotator variability. Variations in ulcer boundary terms, for instance, induced the DFUC2021 dataset to demonstrate a decline of 15% in segmentation model performance during external validation.[62] Often, reliable annotations call for arrangement among several experts, a labor-intensive procedure that blocks dataset growth and strengthens the need for fragmented samples.[15,62]

Obstacles in Clinical Practice and Technology

Despite advancements in image-based diagnostics, many AI algorithms, especially those dealing with visually modest or similar features such as wet and dry gangrene, are struggling to properly determine the severity of the disease and could be impacted by shifts in image-capturing techniques or devices.[21,63] Hardware makes practical deployment extremely tough. Low-cost thermal sensors in smartphones usually lack the accuracy (<1°C) required to identify early ischemic changes, and wearable pressure sensors could overlook microtrauma-inducing spikes in neuropathic patients.[55,64,65] Smartphone-based gangrene detection models in a Tanzanian experiment missed 20% of early-stage patients because of inadequate image resolution.[46] The current technological shortcomings underscore the

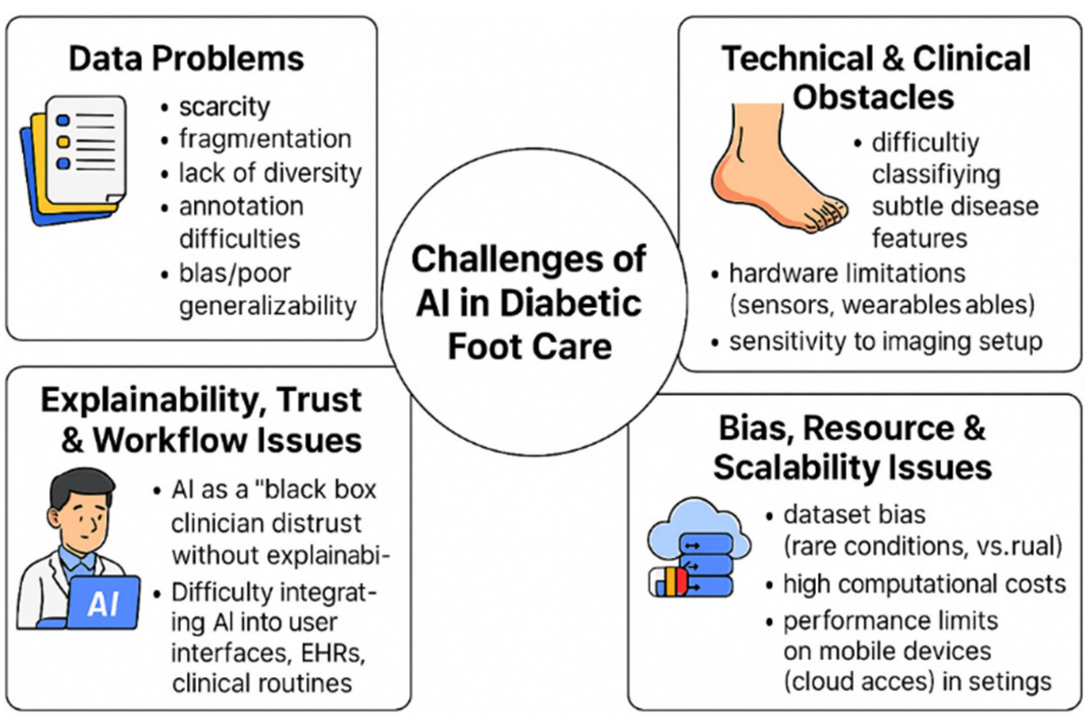

Fig 6 | Key challenges of AI implementation in diabetic foot care

necessity for hardware solutions that are both resilient and flexible. These systems must be designed to accommodate the varied demands of different clinical settings.

Explainability, Trust, and Workflow Integration

Transparency and explainability continue to be some of the most significant hurdles in clinical AI adoption. Several deep learning models are simply "black boxes," which makes clinicians understandably concerned, especially when dealing with critical cases like gangrene detection. Although tools like Grad-CAM and XAI-FusionNet are trying to fix this, most medical AI still do not supply clear answers about why most clinical AI technologies still lack explainability.[41] Take that survey of 200 dermatologists—nearly 70% said they would not fully trust AI's assessments of DFUs unless the system showed them heatmaps or something visual to back it up.[41] The other big issue is getting AI to work in real hospital settings. For health care professionals to use this technology effectively, it needs to have simple interfaces that do not slow them down. AI tools must interface with electronic health records and align with existing care protocols without disrupting efficiency.[21]

Scalability, Resource Limitations, and Bias

AI has the potential to significantly transform the landscape of scalable, cost-effective care for DFUs and gangrene. It would speed up and simplify the process while reaching more people who need care. Let us acknowledge that technology is not perfect. Yet, its power is often restricted by resource limits and bias that skew outcomes. One major issue is that the AI does not always get trained on rare conditions like gas gangrene or Charcot foot, so it might miss those cases. Models created and validated with data from big city hospitals often flop in rural areas. Those places already have it rough—not enough specialists, slow medical help, and even food shortages. High-resolution imaging, while refining analytic accuracy, demands important computational resources, making immediate analysis on mobile devices inspiring.[41]

According to Wagobera Edgar Kedi et al.,[65] areas missing cloud computing infrastructure still experience diagnostic disruptions and rely on subjective clinical judgments. Without addressing these gaps, the benefits of AI may remain unevenly distributed, hence boosting prejudice and restricting the actual application of AI tools for the diagnosis of DFU.[46]

Future Directions

The ongoing advancement of AI in diabetic foot care brings both opportunities and complexities. While these technologies hold promise for improving early diagnosis and enabling personalized therapies for DFUs and gangrene, clinical adoption is not straightforward—implementation involves navigating practical hurdles that go beyond technical capabilities, including privacy issues, scalability in diverse health care environments, explainability for clinician trust, and ethical considerations, especially for vulnerable patient populations and resource-limited environments. As AI becomes more embedded in patient care, it is essential to address these factors to ensure that innovative solutions translate into meaningful improvements in outcomes across all clinical contexts. Key steps toward achieving standardized DFU management with AI integration are illustrated in Figure 7.

Clinical Workflows and XAI

Promoting clinician trust and ensuring the secure use of AI in diabetic foot care requires the implementation of dynamic explainability tools into health care workflows. The real-time Grad-CAM heatmap era, as seen in cancer diagnosis systems, may enhance clinician-AI collaboration by offering immediate visual feedback during the monitoring of patients. During telemedicine consultations, for instance, the incorporation of Grad-CAM into mobile-based gangrene detection systems might highlight necrotic zones in photos captured by smartphones. Remote consultations using real-time telemedicine reduce the delay between requests for consultations and their completion, reduce nonproductive staff time and transportation costs, and are comparable to traditional face-to-face consultations.[66,67] XAI into routine practice is essential for clinician acceptance and patient safety.

Privacy-Protecting FL

One innovative approach that safeguards the confidentiality of patients while training AI models for health care is FL. FL allows collaborative modeling through organizations by training algorithms on decentralized datasets without transferring raw patient data by following rigorous rules, including GDPR and HIPAA. Combining FL with blockchain technology increases the security and openness of medical data sharing. Compared to traditional CNNs, FL-HMChain achieved a 4.7% increase in AUC and 7% improvement in accuracy for medical image analysis by securing local-global model interactions.[43] Yet, challenges such as data heterogeneity, computational complexity, and possible information leakage offer diagnostic obstacles for DFUs and gangrene.[68] Future initiatives ought to concentrate on standardizing dataset formats, which include explainability tools like Grad-CAM, and developing regulatory systems that guarantee ethical use globally.[69,70]

Multimodal Sensor Integration for DFU Management

Preserving complementary physiologic perspectives, the integration of multisensor data, such as plantar pressure, infrared thermography, and electrochemical markers—has transformed early detection and individual treatment of diabetic foot obstacles. Projects like DiaSense monitor ulcer risk in real time by combining plantar pressure sensors and infrared thermography with AI algorithms, therefore achieving >90% accuracy in detecting unconventional pressure distributions and temperature asymmetries.[25,71] Hybrid architectures such as DE-ResUNet, which integrate RGB and thermal imaging using FL, have shown 97% IoU in

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Fig 7 | Roadmap to achieving standardized DFU management with AI integration

ulcer segmentation, outperforming single-modality approaches by 18%.[31,72] By analyzing tissue oxygenation (StO_2) and hemoglobin levels to forecast ulcer healing, hyperspectral imaging complements tissue oxygenation and hemoglobin, therefore adding further prognostic value. Wearable solutions like AI-embedded insoles created in the DiaSense Project use photovoltaic-powered sensors for ongoing monitoring of plantar pressure and temperature, hence allowing real-time monitoring of high-risk regions. Future systems seek to combine edge computing with TinyML frameworks to locally process multimodal data (pressure, temperature, and gait) on devices, hence lowering cloud reliance, minimizing latency, and improving privacy—critical for remote and resource-limited environments.[18]

Strategies for Successfully Scaling Global Access

Scalability is going to continue in promoting global adoption of AI-driven diabetic foot care technologies, particularly in resource-limited settings. Lightweight platforms and synthetic data approaches are mandated to reach this objective. Techniques such as quantization (decreasing mathematical precision) and pruning (eliminating redundant neural network masses) allow real-time analysis on smartphones and edge devices. For example, TensorFlow Lite models, while performing on mid-range GPUs such as the NVIDIA GTX 1650, reduced memory consumption by 40% with less than 2% performance loss, comparable to cloud-based systems.[73] Quantized MobileNetV2 for smartphone deployment achieves 80.65% accuracy, demonstrating feasibility for real-time applications in clinics with few resources.[74]

To compensate for the shortage of datasets, GANs generate uncommon ulcer subtypes (such as gas gangrene) and achieve an accuracy rate of 84% when detecting ulcers. Hybrid frameworks like ResNet50-GAN provide realistic synthetic images while maintaining pathological characteristics, enhancing model generalizability across diverse populations. As illustrated by multimodal systems integrating thermal and RGB images, FL boosts scalability even more by facilitating privacy-preserving collaboration across organizations.[73]

Collaboration and Ethical AI Implementation in Diabetic Foot Care

Ensuring equitable and responsible deployment of AI in diabetes foot care requires standardized protocols, rigorous validation, and multidisciplinary collaboration. The DFUC2021 consortium highlights such an approach by gathering multi-institutional data (15,683 annotated pictures from Lancashire Teaching Hospitals) for creating benchmarks for the effectiveness of models and mitigating dataset biases in ulcer subtypes and skin tones.[38] These efforts maximize generalizability, particularly for populations underrepresented in regions with low resources and high diabetes incidence.[45,75] Ethical deployment calls for established procedures, legal compliance (e.g., GDPR/HIPAA), and explainability tools such as Grad-CAM heatmaps to build clinician confidence.[45,75,76]

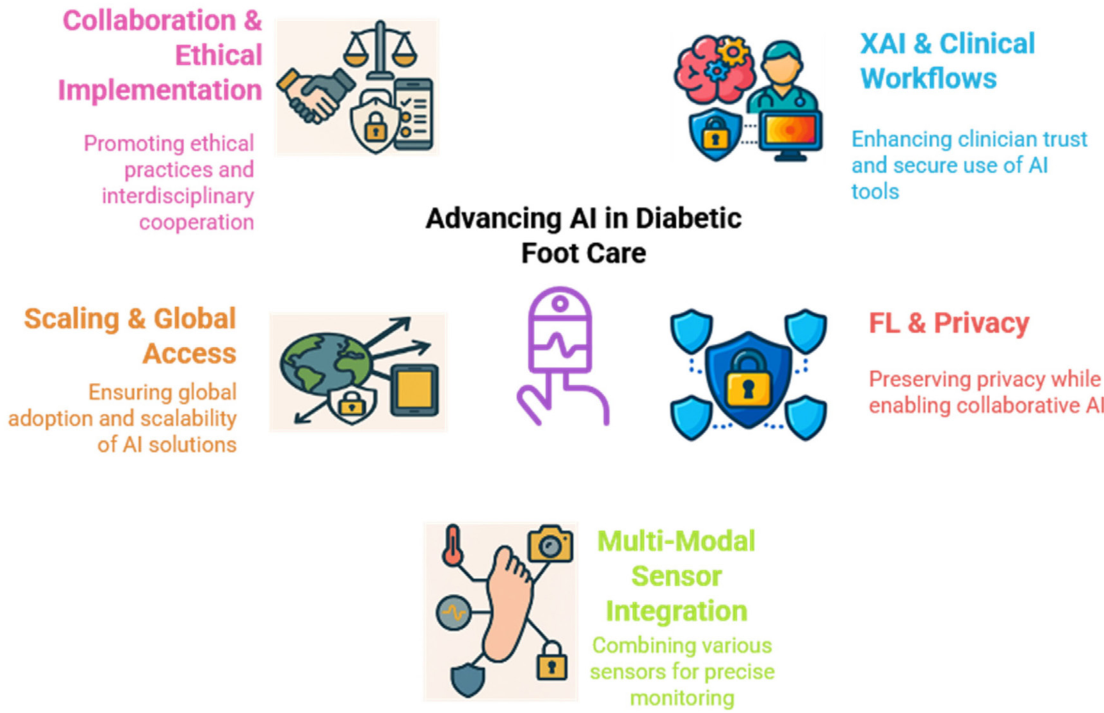

Fig 8 | Key pillars for advancing AI in diabetic foot care

Ensuring that new technology fits with actual world processes depends on clinician participation in AI design. Surveys show that most doctors do not believe AI-generated results unless backed by understandable visual explanations, hence stressing the importance of human-AI cooperation in system development.[45] Prospective, real-world validation is fundamental, as evidenced by platforms like DFUCare, which indicated high accuracy in research trials but displayed restrictions, including a 20% false-negative rate in rural Tanzania when carried out in various circumstances.[45,47] AI and multimodal sensors are employed in multidisciplinary initiatives that underscore the beneficial effects of collaborating to deal with ethical concerns as well as improving diagnostic precision.[47,77] Overcoming the discrepancies between advancements in AI and equitable, high-quality diabetic foot care mandates a successful handling of limited resources, data bias, and an urgent need for global regulatory harmonization. The key pillars for advancing AI in diabetic foot care—including collaboration, ethical implementation, clinical workflow integration, privacy, global access, and sensor integration—are illustrated in Figure 8.

Conclusion

AI is rapidly transforming diabetic foot care by enabling earlier detection, more accurate classification, and personalized management of DFUs and gangrene. Notable achievements include the integration of hybrid deep learning models, multimodal sensors, and privacy-preserving frameworks such as FL, which collectively enhance diagnostic accuracy and support real-time, scalable health care delivery. However, despite these advances, most AI successes for DFUs and gangrene still rely on single-center or homogeneous datasets, resulting in data scarcity, annotation inconsistency, limited generalizability, and bias—particularly in resource-limited settings. These issues, along with high technical demands, currently impede routine clinical use and widespread adoption.

To bridge the gap between technological promise and widespread patient benefit, future research must focus on assembling diverse, well-annotated datasets, conducting rigorous external validation, and embedding model explainability and trust-building measures into AI tools. Collaborative innovation in these areas will enable AI to equitably improve diabetic foot complications and optimize quality of life for patients worldwide.

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