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Review Article

Addressing Identification Deficiencies in Diabetic Foot Ulcers: A Systematic Review of Techniques and Solutions

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ABSTRACT

Diabetic foot ulcers (DFUs) present a critical challenge in diabetes care, often leading to severe infections and amputations due to delayed diagnosis. This systematic review aims to address gaps in DFU detection by evaluating emerging technologies designed to enhance early identification and improve patient outcomes. Implementing the PRISMA guidelines, 59 studies were selected for comprehensive analysis, focussing on the efficacy and clinical applicability of biomarkers, artificial intelligence (AI) and machine learning (ML) tools, and handheld diagnostic devices. Results indicate that biomarkers, such as procalcitonin, hold promise for detecting infections at an early stage. Moreover, AI and ML-based techniques substantially improve diagnostic accuracy and enable remote monitoring, facilitating timely intervention. However, challenges in integrating these technologies into routine clinical workflows persist due to cost, scalability, and infrastructure issues. Continued research is essential to address these limitations, ensuring that advanced DFU detection methods can be implemented effectively in diverse healthcare settings.

Keywords: Artificial intelligence, biomarkers, clinical integration, diabetic foot ulcers, early detection, machine learning

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INTRODUCTION

Diabetic foot ulcers (DFUs) present a critical global health challenge, affecting approximately 15% of individuals with diabetes over their lifetime (Minty et al., 2023). These ulcers can lead to serious complications, including infection, gangrene, and even amputation, if not addressed effectively (Kunta et al., 2022).

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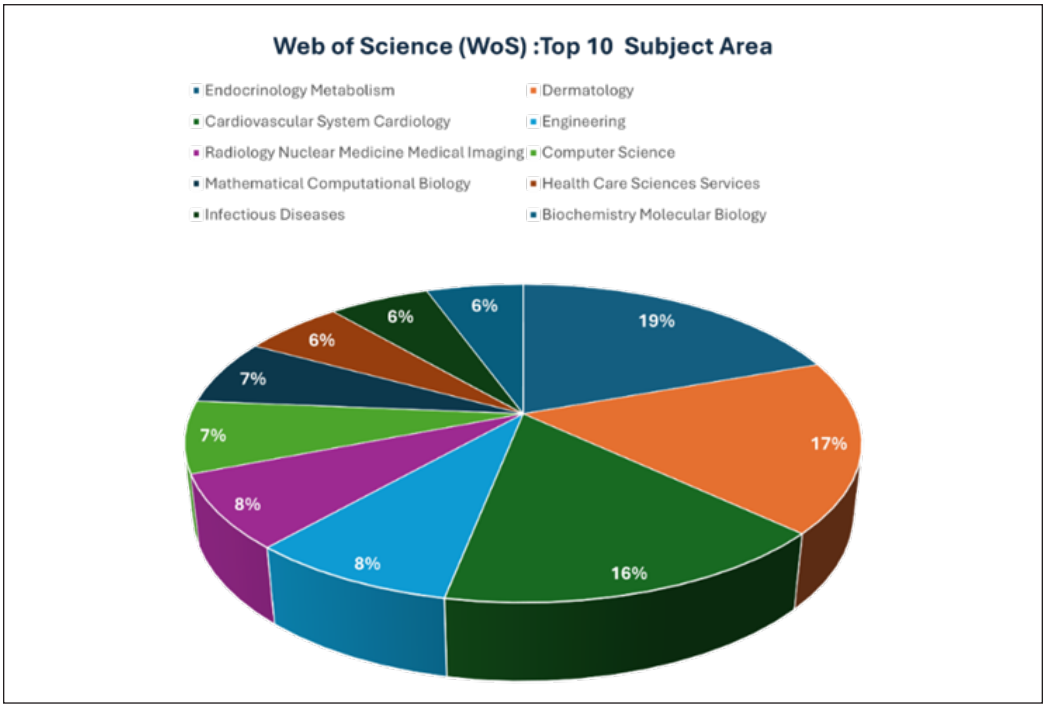

Figure 1. Distribution of top 10 subject areas in the Web of Science (WoS)

As such, DFUs represent a significant unmet healthcare need, particularly in regions with limited resources, where access to timely and effective care may be restricted (Armstrong et al., 2023). The expeditious identification and comprehensive assessment of DFUs are crucial for managing patient outcomes and reducing the risk of complications. However, traditional diagnostic methods, including visual inspections and imaging for bone mineral density (BMD), often lack the precision required for early intervention, particularly in asymptomatic cases of diabetic peripheral neuropathy (DPN) (Doğruel et al., 2022; López-Moral et al., 2022).

In recent years, the need to enhance diagnostic accuracy for diabetic foot ulcers (DFUs) has prompted the development of novel technologies and methodologies. This has attracted the attention of various fields of study related to diabetic detection, as illustrated in Figure 1. Highlights the multifaceted approach necessary for addressing DFU-related challenges (Mamdoh et al., 2023). Despite advancements, effective detection remains a challenge, particularly in identifying early neuropathic changes that may signal a higher risk of ulcer development. This gap in the current healthcare landscape has spurred innovation in DFU detection technologies, emphasising non-invasive, scalable solutions that can be integrated across various healthcare settings.

Several emerging technologies show promise in addressing the limitations of traditional DFU diagnostics. Functional magnetic resonance imaging (fMRI) has been investigated for its potential to detect early neurological changes associated with DPN. It provides a noninvasive means of identifying patients at heightened risk for DFUs (Chitneni et al., 2022). Additionally, advanced imaging techniques, such as the convolutional neural network framework as modelled in Figure 2, "DPN-Net," utilise thermographic imaging to enhance the detection of DPN in its early stages, which could aid in the proactive management of DFUs (Evangeline & Srinivasan, 2024). These technological advancements align with the growing need for cost-effective and adaptable methods that can be implemented in diverse healthcare settings, including those with limited resources.

Biosensor technology represents another promising frontier in DFU diagnostics. Shobana et al. (2023) introduced a biosensor incorporating cerium titanate oxide-doped carbon dots, capable of detecting L-tyrosine—a biomarker indicative of DFU infections—with high sensitivity. This advancement could facilitate earlier diagnosis, potentially before clinical symptoms become visible. Similarly, fluorescence imaging has been shown to detect bacterial biofilms in DFUs, offering a noninvasive approach to identify infections at an incipient stage (Armstrong et al., 2023). By enabling the early visualisation of bacterial presence, these techniques could transform DFU management by allowing timely intervention and reducing the risk of severe infections.

Wearable technology has also been explored as a means to monitor and manage DFU risk, particularly in the context of diabetic peripheral neuropathy (DPN). Brognara et al. (2023) demonstrated the utility of wearable sensors in tracking postural stability, a factor linked to DPN. Such real-time monitoring capabilities could be instrumental in predicting DFU risk, enabling clinicians to implement preventative measures proactively. This aligns

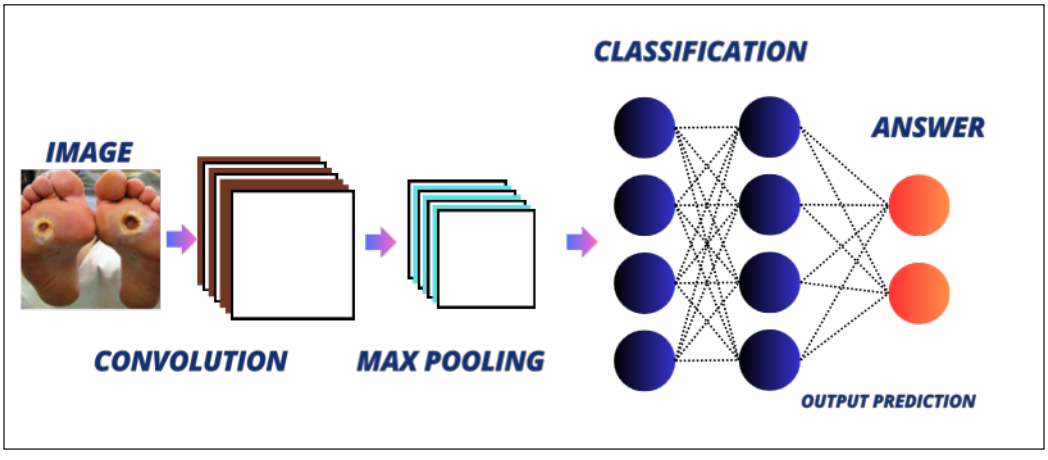

Figure 2. Convolutional neural network neural network framework

with broader goals in diabetic foot care, emphasising early intervention and continuous monitoring as key strategies for reducing the incidence and severity of DFUs.

While several review articles on the subject of emerging DFU detection approaches have been recently published, some of these review articles are either too broad (including research areas outside of the context of DFU diagnostics, such as other aspects of wound care and monitoring), too dated (surveying research articles many years before those included in the present study), or too specific to some technological areas (covering only wearables or only artificial intelligence), to be considered fully representative of the field of research as a whole. Rismayanti et al. (2022) published a systematic review and analysis of the research studies that describe the early detection of foot ulceration in type 2 diabetes patients to obtain insight into the prevention of diabetic foot ulceration. The study considered research literature published until the end of 2021. Chan and Lo (2020) published a systematic review of wound assessment, imaging, and monitoring systems used in the management of diabetic foot ulcers (DFUs). Sidhu and Harbuzova (2024) published a review on emerging technologies for clinical management of diabetic foot ulcers, including their use in both diagnostics and monitoring of treatment response. Lazarou et al. (2024) published a scoping systematic review of novel sensor technologies and health outcomes in patients with diabetic foot ulcers, including a specific section on wearable systems. While all of these review articles provide some valuable context and insight into some aspect of the field of study, this review article is unique in that it provides a comprehensive and up-to-date survey of the most recent and relevant research studies on emerging approaches to DFU detection (published between 2022 and 2024), including next-generation sensing platforms and materials, wearable monitoring systems, thermal imaging modalities, and artificial intelligence–driven diagnostic systems. The narrower focus of this review article on emerging and current approaches to DFU detection, while still being sufficiently broad to encompass the main categories of relevant research, enables a more in-depth examination of the state-of-the-art trends and innovations currently driving the field.

Given these advancements, this systematic review aims to evaluate the effectiveness, accessibility, and potential for clinical integration of emerging DFU detection technologies. By examining methods such as biosensors, thermal imaging, and wearable devices, this review aims to bridge the gaps in DFU diagnostics and provide a comprehensive overview of scalable solutions that can improve patient outcomes. Additionally, this study will examine the barriers to implementation, particularly in resource-constrained healthcare settings, and assess the feasibility of integrating these technologies into routine clinical practices. This paper decisively addresses three essential research questions outlined in Figure 3.

By synthesising the existing literature, this review will provide valuable insights into the current state of DFU detection technologies, their practical applications, and their potential to transform the management of DFU across various healthcare settings.

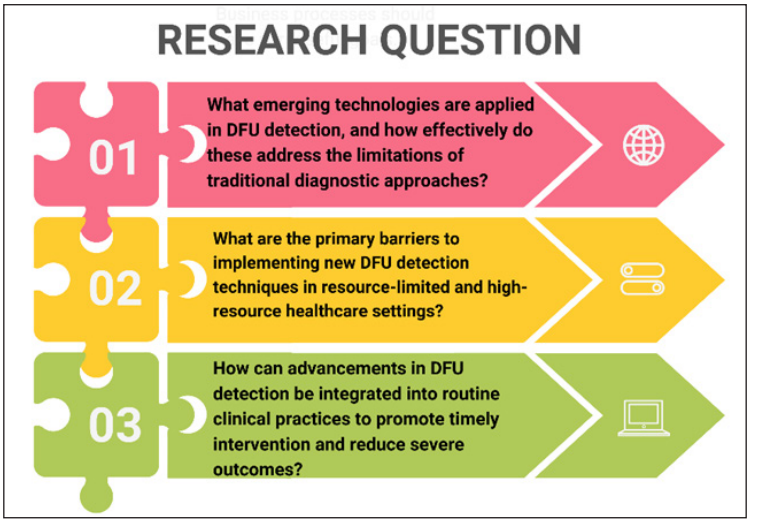

Figure 3. Research questions on emerging technologies and practices in DFU detection

MATERIALS AND METHODS

This systematic review employs a rigourous methodology based on the Systematic Literature Review (SLR) framework to comprehensively examine current research on diabetic foot ulcer (DFU) detection techniques. This review ensures that only relevant and high-quality studies from reputable academic sources are included by utilising a structured tri-phasic approach to identification, screening, and eligibility. The process is illustrated in Figure 4, which outlines the SLR methodology applied in this study.

Identification

A tripartite methodological framework was designed to select pertinent literature in the identification phase. This preliminary stage focussed on developing a comprehensive list of keywords, informed by thesauri, previous studies, encyclopedias, and specialised lexicons related to DFU detection. Once relevant keywords were identified, search strings were formulated and utilised in the SCOPUS and Web of Science (WoS) databases. This initial search yielded 1,106 articles (455 from SCOPUS and 651 from WoS), constituting the foundational dataset for this review.

Screening

The second phase, screening, prioritised precision and consistency in selecting studies that met specific inclusion and exclusion criteria established by recognised experts in the field. During this stage, 294 articles were selected for evaluation based on these criteria, which included:

- Research articles only.
- Studies published in English to ensure language consistency.
- Publications are limited to the last three years (2022–2024) to maintain relevance to the latest advancement of DFU detection.

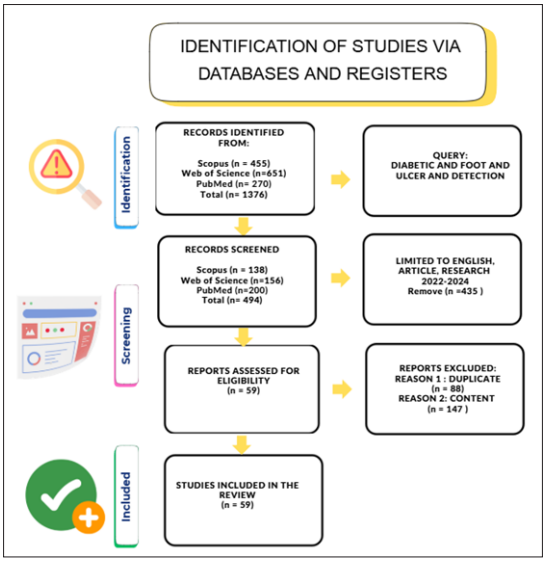

Figure 4. PRISMA flow diagramme for study selection in DFU detection research

During this process, 88 duplicate articles were removed, and 147 additional studies were identified based on strict selection criteria. This left a refined pool of articles for in-depth examination.

To enhance the sensitivity of the search strategy, a manual search was conducted on the PubMed database, yielding 270 additional records. For this systematic search, all original articles were selected. The research articles, review papers, editorials, letters, and non-English texts have been excluded from this review. Manuscripts lacking methodological rigour and unrelated articles, as well as studies on DFU detection technologies, have been excluded, along with duplicate records in two databases. The final screening was limited to studies published between 2022 and 2024, with the primary focus on advancements in biosensor systems, wearable monitoring devices, AI-integrated diagnostics, and thermal imaging to support the validity of the evidence.

Eligibility

In the final phase, eligibility, the remaining 59 articles underwent a detailed assessment to determine their suitability for inclusion. Each article was evaluated based on its title, abstract, and primary content to ensure alignment with the inclusion criteria and the review's overarching objectives. This meticulous assessment ensured that only the most relevant studies directly addressing the study's aims were retained for the final analysis.

Data Abstraction and Analysis

The data abstraction and analysis process utilised an integrative approach to evaluate various research designs, including quantitative, qualitative, and mixed-methods studies, as illustrated in Figure 4. The analysis was conducted systematically to document and synthesise all findings and interpretations relevant to DFU detection. This approach

enabled a comprehensive evaluation of the strengths, limitations, and clinical applicability of various DFU detection techniques, providing a nuanced understanding of the current state of research in this domain.

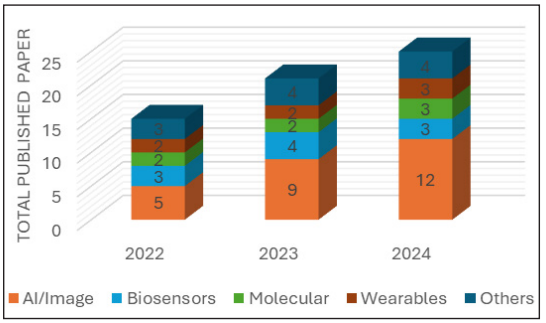

Figure 5. Trend of publication

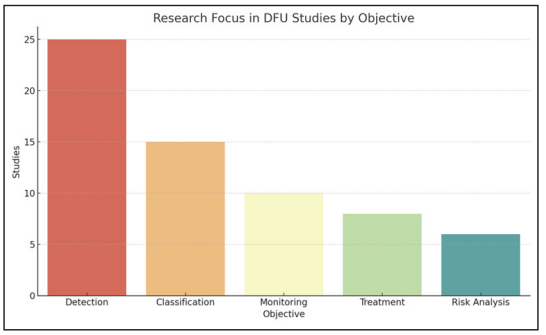

Figure 6. Research focus in DFU studies

RESULTS AND DISCUSSION

The rising prevalence of diabetes worldwide and the significant consequences of undiagnosed or poorly managed Diabetic Foot Ulcers (DFUs) have made their detection a topic of considerable interest in recent research. Traditional diagnostic strategies rely heavily on visual inspection and physical examination, which are limited by subjectivity and low sensitivity and specificity (Chemello et al., 2022; López-Moral et al., 2022). New technologies (machine learning algorithms, imaging modalities, biosensors, and biomarkers) offer potential avenues for early detection with fewer of these limitations (Chemello et al., 2022; Omar et al., 2023).

A total of 59 studies were included as shown in the Appendix, based on strict inclusion criteria to encompass the breadth of DFU detection techniques being explored. Each study was categorised based on primary objectives, methodology, specific detection techniques, and key findings. As shown in Figure 5, the number of publications per year has increased from 2022 to 2024, with the most significant proportion of papers on AI and imaging-based techniques (rising from 5 in 2022 to 12 in 2024). This suggests that DFU detection is increasingly shifting towards intelligent and automated methods. The number of studies on biosensors, molecular diagnostics, and wearable technologies has remained relatively stable over this period, suggesting that these areas are still in the process of emerging in terms of clinical applicability. The "Others" category, which includes traditional screening tools and clinical frameworks, has remained consistently present, reflecting the continued importance of scalable and accessible detection solutions. This analysis demonstrates that the review is timely, as it captures the shifting research areas and reflects the transformation from traditional methods to technology-based DFU detection solutions.

To characterise the functional areas addressed by the literature included in the review, Figure 6 provides a categorical breakdown of the primary objectives identified in each of the included studies. This classification was performed systematically during data extraction, based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analyses) guidelines. The majority of the included studies (n = 25) focussed on DFU detection, indicating that this remains the most common area of research focus in recent years. A large number of studies (n = 15) also addressed classification, often through ulcer severity scoring and pattern recognition. Finally, a smaller number of studies focussed on treatment evaluation (n = 8) or risk analysis (n = 6) – for example, identifying predictors of ulcer recurrence or risk of amputation. (Note that because some studies had multiple objectives, the total number of objectives is higher than the number of articles.)

In the context of a PRISMA-guided review, this categorisation of the objectives is critical to ensure transparency, reproducibility, and relevance. For researchers, it provides a structured understanding of the functional distribution of technological and clinical objectives being pursued, highlighting underrepresented areas that could be targeted for future development. For academics and funding bodies, it provides a decision-making framework to understand imbalances across the research spectrum. For example, while many studies address DFU detection, post-diagnostic management, and predictive analytics are significantly underdeveloped. This data-driven perspective can be used to better direct future research efforts towards more targeted, interdisciplinary, and clinically relevant applications.

A meta-analysis of diagnostic performance across the included studies was also conducted based on reported sensitivity and accuracy metrics. As shown in Figure 7, the performance of DFU detection techniques varied widely depending on the methods applied. Deep learning methods, particularly convolutional neural networks (CNNs), showed the highest accuracy and sensitivity values, often above 95% for both metrics. AI-integrated systems and mobile health applications also showed consistently high performance, with sensitivity values above 85% and accuracy in the range of ~90% to 94%. Thermal imaging, biosensor-based methods, and hybrid machine learning methods, with imaging, reported moderate-to-high accuracy (~85%–93%) and corresponding sensitivity values in the range of ~80% to 88%. Techniques for biomarker detection (measuring procalcitonin levels) showed moderate sensitivity (~75%) and high accuracy. Finally, wearable devices and functional MRI-based methods showed lower performance with sensitivity values below 70% and accuracy in the range of ~64–75%.

Taken together, these results provide a comprehensive understanding of the current landscape of DFU detection research. The increasing number of publications from 2022 to 2024 (Figure 5), the diversity of study objectives (Figure 6), and the variable diagnostic performance across techniques (Figure 7) all reflect a shift towards innovation-driven

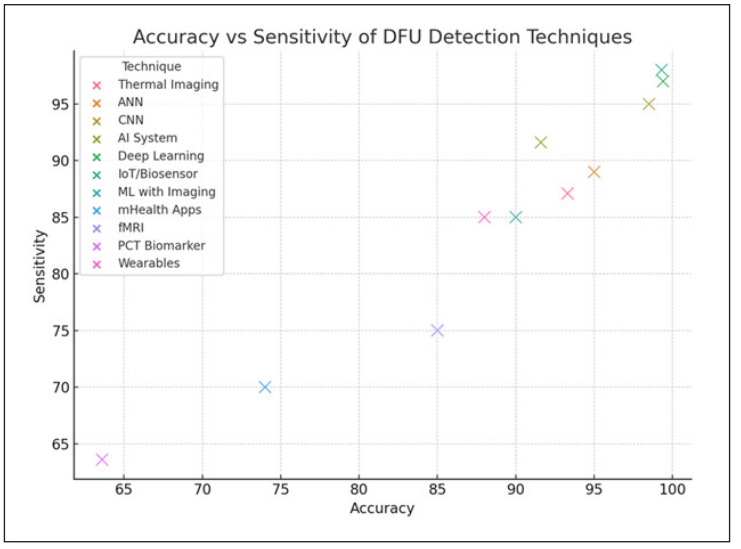

Figure 7. Scatter plot presenting the reported accuracy and sensitivity values for DFU detection techniques extracted from included studies, categorised by method type

DFU detection. While DFU detection is the most common focus, the high variability in methodology, outcome metrics, and translational readiness highlights the need for a critical evaluation of these emerging technologies. (1) emerging technologies that enhance detection capabilities, (2) integration of these technologies into clinical practice, and (3) barriers that impede their adoption.

Emerging Technologies in DFU Detection

Emerging technologies, such as biosensors, artificial intelligence (AI), thermographic imaging, and molecular diagnostics, have been demonstrated to be of significant importance in overcoming some of the limitations of existing DFU diagnostic methods. These technologies can facilitate the more precise, sensitive, and non-invasive detection of DFU. The four technologies discussed in this review are designed to facilitate the early detection of DFU and prompt effective clinical management.

Biosensors stand out due to their capability to precisely and sensitively detect biomarkers of infection that are crucial for early-stage detection. Carbon-dot-doped cerium titanate biosensors have been reported to detect the presence of L-tyrosine at nanomolar concentrations, enabling the fast and non-invasive detection of infection (Shobana et al., 2023). Molecular diagnostic methods, such as roll-to-roll DNA nanomachines, facilitate ultra-sensitive detection of infection markers. These play a crucial role in the early detection of infection, often before any symptoms are visible (Chemello et al., 2022; Hnit et al., 2022). The use of AI for DFU detection, particularly CNN and Fast R-CNN, has been widely

adopted in most studies and can perform tasks that were previously carried out manually. The models provide high levels of accuracy and quick diagnosis. AI-based methods are also effective in detecting the location and severity of DFU and often outperform conventional methods (López-Moral et al., 2022; Nagaraju et al., 2023). Thermographic imaging combined with machine learning is a practical approach for mapping plantar foot temperatures, facilitating the early detection of neuropathic complications. This method is effective in regions where advanced imaging equipment is not readily available (Evangeline & Srinivasan, 2024; Rossboth et al., 2022). Molecular diagnostics can also facilitate the early detection of DFU by utilising the presence of the serum procalcitonin (PCT) biomarker, enabling rapid decision-making. This enables clinicians to intervene before the onset of clinical symptoms, thereby reducing diagnostic delays (Omar et al., 2023). All of these technologies aim to achieve the goal of this systematic review, which is to analyse new methods that can help address the existing limitations of conventional DFU detection methods. The contributions of these methods are similar to those observed in recent studies. This includes the increased automation, sensitivity, and non-invasiveness of the diagnostic methods (Brognara et al., 2023; Viswanathan et al., 2024). Some of the limitations common to the reviewed studies include variability in methodological rigour, inconsistent reporting of study protocols, and the lack of longitudinal outcomes to evaluate the efficacy of these technologies. There may also be selection or reporting biases in the reviewed studies, which could affect the reported outcomes. Despite the findings of these technologies, further research is needed to validate their long-term efficacy and integrate them into clinical practice.

Integration of DFU Detection Advancements into Routine Clinical Practices

Despite recent technological advances in DFU detection, its integration into routine practice has remained inconsistent across different healthcare systems. At the community level in low-income settings and the point-of-care level in high-income settings, the effective translation of DFU detection technologies is hindered by infrastructure, funding, and behavioural challenges rather than by the technology itself.

In resource-limited settings, community-based screening with the “Diabetic Foot Check-up” could be an effective way to identify patients at risk of DPN. While promising, its implementation is constrained by limited funding, inadequate provider training, and low political support (Habibu et al., 2022). In Ethiopia, the lack of available foot screening devices has led to delayed diagnoses and more preventable complications (Tegegne & Wubante, 2022).

Even in high-income settings, where diagnostic technologies are readily available, persistent barriers remain. For example, in resource-rich regions of Canada, access to

podiatric care varies significantly by region and within regions, and is not distributed equitably (Rai et al., 2022). For instance, podiatrist-led management is effective in reducing amputations; however, it is only feasible if there is access to podiatrists, which is more challenging in rural and underserved regions (Rai et al., 2022). Financial barriers are also a universal issue; for example, although the Diabetic Foot Screen Proforma was found to be cost-effective in a study in Myanmar, dedicated funding mechanisms have been slow to develop (Hnit et al., 2022). Even in a dialysis unit where patients at high risk for DFUs are identified, regular foot health checks are not always conducted (Viswanathan et al., 2024).

Furthermore, the impact of DFUs on the personal and social well-being of patients illustrates the importance of early detection. Patients with DFUs in Nigeria showed significantly lower scores in physical function, emotional well-being, and social participation compared to those without DFUs, which could have been prevented if detected earlier (Habibu et al., 2022). Despite the existence of nationwide screening campaigns, such as the "Save the Feet and Keep Walking" campaign in India, public awareness and engagement in prevention remain lacking (Balasenthilkumaran et al., 2022; Viswanathan et al., 2024). Additionally, cultural beliefs, stigma, and low health literacy have all contributed to patients' reluctance to seek care, underscoring the need for patient-centred education tailored to the local context (Kumsa et al., 2023).

The key question that still needs to be addressed is why, if state-of-the-art DFU detection systems can achieve up to 95% diagnostic accuracy in clinical settings (Muthuraja et al., 2024; Nagaraju et al., 2023), amputations continue to occur at high rates in certain regions. This difference in technological capacity and clinical outcomes shows a clear gap between the promise of technology and its effective translation into clinical practice. It also shows that even high-performing technologies will not make a difference unless they are successfully translated into practice, with the necessary infrastructure, and accepted by providers and patients.

Primary Barriers to Implement New DFU Detection Techniques

Although all of the above technologies have promising diagnostic potential, their adoption in practice is currently limited by various implementation barriers. Although the approaches that use AI-driven analysis, biomarker profiling, and remote monitoring all have high diagnostic performance, they are limited by structural, technical, and socioeconomic factors in practice.

For example, despite its high performance, biomarker profiling (which includes antimicrobial susceptibility testing and bacterial strain identification) may be challenging to implement at the point of care in low-resource settings because of its requirement for sophisticated laboratory infrastructure that is often not available in primary care settings (Armstrong et al., 2023). Similarly, screening methods that target the presence of virulence

factors, such as the Panton–Valentine leukocidin (PVL) gene in Staphylococcus aureus, can guide the selection of an antibiotic strategy; however, this is limited by the need for specialised equipment and associated costs (Pany et al., 2022).

Similarly, patient-centred innovations, such as mobile applications, can enable people to monitor their risk of DFU and share their data with clinicians in real-time, reducing the burden of in-person visits (Rismayanti et al., 2022). However, these innovations can be challenging to implement in practice if individuals lack access to smartphones, are digitally illiterate, or have difficulty communicating with their clinicians in their preferred language. Thus, despite technical feasibility, the benefits of these tools are unevenly realised, even in settings where they are feasible.

Similarly, remote monitoring systems (such as cloud-based diagnostic platforms powered by deep learning) can increase DFU surveillance in underserved areas by automating image analysis and providing decision support (Cassidy et al., 2022). However, their effectiveness in practice depends on having reliable internet access, compliance with data privacy laws, and adequate user training. Additionally, although AI-driven diagnostic systems can be highly accurate, they are limited by scalability challenges related to computational cost, the need for large standardised datasets, and a lack of external validation in various patient populations (Cassidy et al., 2023; Yogapriya et al., 2022).

Similar technologies, which involve advanced imaging (such as hyperspectral analysis and predictive biomarker mapping), have also been explored to assess the severity of DFU and predict healing trajectories (Omar et al., 2023; Zhao et al., 2023). However, the clinical translation of these technologies is limited by their reliance on expensive sensors, the complex data interpretation algorithms required, and their limited applicability in the point-of-care setting.

Cost-related limitations are also a key barrier to the adoption of new DFU detection technologies. Several of the reviewed technologies are limited by their costs in practice despite their high diagnostic accuracy. AI-driven systems, for example, often require high-performance computing hardware, regular model training, and specialised personnel, which make it challenging to implement in primary care settings without a significant sustained investment (Cassidy et al., 2023). Similarly, advanced biomarker analysis (such as bacterial culture profiling and gene-based detection) is limited by the high costs of reagents, laboratory equipment, and validation protocols, and is typically restricted to well-funded tertiary centres (Armstrong et al., 2023; Pany et al., 2022). Advanced imaging methods that use hyperspectral and high-resolution thermographic technologies are also limited by their costs, despite their high precision and non-invasive nature. Their hardware and software requirements necessitate a significant capital investment beyond the reach of many small clinics or rural hospitals (Evangeline & Srinivasan, 2024; Zhao et al., 2023). Additionally, although mobile health platforms and remote monitoring systems can be

inexpensive relative to other technologies, they can have indirect costs (such as software maintenance, user training, and ongoing technical support) (Agustini et al., 2022). Although these digital tools are scalable, large-scale national or regional implementation is not based on formal cost-benefit analyses or health economic modelling.

Few of the reviewed studies contained cost-effectiveness evaluations, and even those that included economic data did so within small pilot programmes rather than large-scale implementation (Hnit et al., 2022). This gap in economic evidence makes it difficult for policymakers and healthcare administrators to make informed decisions on how to allocate resources. This uncertainty about economic viability limits the translational potential of technologies that are otherwise clinically effective. Therefore, there is a need for greater emphasis on economic evaluations (such as cost-utility analyses, multi-setting affordability analyses, and implementation cost modelling) to ensure the sustainable integration of DFU detection technologies. A summary of the costs and practical trade-offs for each technology category is included in Table 1, based on the reviewed studies.

Table 1
Summary of cost-effectiveness considerations for diabetic foot ulcer detection technologies

Technology type	Relative cost	Advantages	Cost-related limitations	Supporting studies
Artificial intelligence-based systems	High	High diagnostic accuracy (≥95%); automation reduces clinical burden	Requires high-performance computing, extensive dataset training, ongoing model updates, and expensive infrastructure	Cassidy et al. (2023); Muthuraja et al. (2024)
Biomarker profiling	High	Enables personalised treatment; detects early infections	Requires advanced laboratories, costly reagents, and complex validation protocols	Armstrong et al. (2023); Pany et al. (2022)
Hyperspectral/ thermographic imaging	Moderate–High	Non-invasive; provides spatial ulcer data for early diagnosis	Equipment and software are expensive, limiting use in rural or low-resource settings	Evangeline & Srinivasan (2024); Zhao et al. (2023)
Remote monitoring platforms	Moderate	Extends diagnostic reach; supports continuity of care in remote areas	Requires stable internet connectivity, ongoing software support, and training for users and providers	Cassidy et al., (2022); Hnit et al. (2022)
Mobile applications for self-assessment	Low–Moderate	Enhances patient autonomy; scalable for community use	Low digital literacy, uneven smartphone access, and user engagement challenges limit effectiveness	Agustini et al. (2022)
Community-based screening tools	Low	Simple and low-cost; suitable for widespread screening	Limited sensitivity and specificity; scalability constrained by gaps in training and funding	Habibu et al. (2022); Tegegne & Wubante (2022)

Future Research

Future research should focus on overcoming existing limitations in DFU detection technologies to facilitate seamless integration into clinical practice, as illustrated in Figure 8. Current challenges include high costs, limited infrastructure, and the need for specialised expertise, which restricts the application of advanced techniques such as biosensors, AI-driven diagnostics, and remote monitoring in both high- and low-resource settings. There is a pressing need to develop cost-effective, scalable models that can be deployed universally, especially in under-resourced areas where DFU cases often go undetected until advanced stages. The integration of machine learning frameworks with real-time tracking and alert systems, as shown in Figure 7, holds promise for continuous patient monitoring and timely intervention, which could significantly reduce DFU-related complications. Furthermore, future studies should aim to validate AI models across diverse populations and explore hybrid approaches that combine molecular diagnostics with remote monitoring to enhance accessibility and improve patient outcomes. Enhanced data-sharing frameworks could support streamlined workflows and facilitate predictive analysis for early DFU intervention.

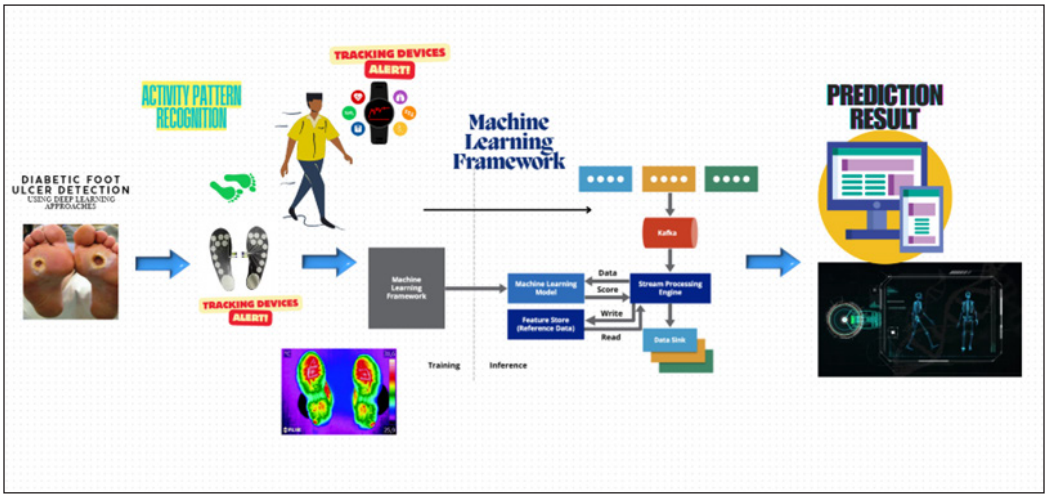

Figure 8. Research future framework for diabetic foot ulcer detection using machine learning and activity tracking

CONCLUSION

This review addresses the research question by demonstrating how advanced diabetic foot ulcer (DFU) detection techniques, including biosensors, artificial intelligence, thermographic imaging, and molecular diagnostics, can mitigate the limitations found in traditional diagnostic methods. These technologies hold significant potential to enhance the accuracy, sensitivity, and accessibility of DFU detection, supporting earlier intervention

and improved management, which are crucial for reducing severe complications and enhancing patient outcomes.

Despite the promise, these techniques face several limitations that hinder broad integration into routine clinical practice. Key challenges include high implementation costs, the need for specialised equipment and trained personnel, and limited infrastructure availability, especially in resource-constrained settings. Furthermore, variability in methodological rigour across studies and a scarcity of data on long-term patient outcomes necessitate careful interpretation of findings.

Future research should focus on developing affordable, scalable models that are adaptable to diverse healthcare environments, particularly in low-resource settings. Validation of AI-driven models across diverse populations is crucial to ensure their effectiveness in various clinical contexts. Hybrid approaches combining molecular diagnostics with remote monitoring could enhance accessibility and enable proactive DFU management.

Additionally, establishing robust data-sharing frameworks may facilitate predictive analytics, allowing for more streamlined workflows and improved patient monitoring. Addressing these areas will be crucial to maximise the impact of emerging DFU detection technologies and make them viable for widespread clinical use.

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Appendix

Summary of each work selected in the PRISMA

Reference	Methodology / Techniques	Sample size and demographics	Key findings	Notable results / Achievements	Comments / Limitations
Agustini et al. (2022)	Non-experimental app development; content validity and reliability testing.	App tested by 5 experts & 30 diabetic patients (Malaysia).	Achieved excellent content validity (I-CVI = 1.00) and good internal consistency (Cronbach's α = 0.74).	The mobile M-DFEET self-assessment app was deemed a valid, reliable early diabetic foot screening tool.	Further studies needed on user adoption and long-term effectiveness; currently validated on a small scale.
Atinafu et al. (2022)	Cross-sectional survey; questionnaires & logistic regression.	N = 283 diabetic patients in Ethiopia (chronic diabetes).	7.1% prevalence of foot ulcers; duration >5 years, prior ulcer, peripheral neuropathy, and certain medications were significant risk factors.	First epidemiological data on diabetic foot ulcers in Ethiopia, highlighting high-risk patient profiles.	Emphasizes need for preventive foot care and early detection in similar low-resource settings.
Balasenthilkumaran et al. (2022)	Thermal foot imaging; asymmetry analysis; ML classifiers (ANN, SVM, etc.).	Thermogram dataset of diabetic patients (not specified; adult population).	ANN classifier accurately identified diabetes (93.3%) and ulcer-prone regions (87.1%).	ANN outperformed other classifiers, suggesting thermal asymmetry can pre-screen for diabetes and foot ulcers.	Demonstrated a non-invasive screening tool for early intervention, potentially before confirmatory blood tests.
Bougrine et al. (2022)	Thermal image segmentation using modified snake algorithm.	Thermal foot images (number not given; diabetic subjects).	Achieved 94% contour similarity in detecting plantar hot-spots.	High accuracy (Dice coefficient 0.94) and low error (~5 pixels) in hyperthermia detection.	Supports early ulcer prediction via mobile-applicable thermal imaging technology.
Brognara et al. (2023)	Wearable sensors + balance tests (Tinetti, Downton); logistic regression.	Diabetic neuropathy patients vs controls (Italy; sample not stated).	Profound neuropathy linked to significant postural instability.	Wearable sensor metrics correlated with neuropathy severity and glycemic control, showing promise for fall-risk assessment.	Highlights potential for wearable devices in routine neuropathy screening and fall prevention in diabetics.

Reference	Methodology / Techniques	Sample size and demographics	Key findings	Notable results / Achievements	Comments / Limitations
Bubun et al. (2023)	Inter-operator observational study (IpTT touch test & pulse check).	144 diabetic patients (Indonesia) assessed by nurses vs caregivers.	No significant difference in touch-test results between nurses and lay caregivers; pulse check sensitivity ~50%.	Demonstrated the Ipswich Touch Test is reliable across operators, supporting community-based foot screening.	Validates a simple, cost-free screening tool feasible for non-clinicians, encouraging wider implementation.
Caruso et al. (2024)	Randomised placebo-controlled trial (liraglutide vs standard care).	N = 55 T2DM patients with PAD (mean age ~67.5; ~78% male).	Liraglutide significantly improved $TcPO_2$ (+11.2 mmHg vs control) and 6-minute walk distance (+25 m) over 6 months.	Nearly 90% of liraglutide group achieved >10% $TcPO_2$ increase vs 46% in control.	Suggests GLP-1 agonist therapy can enhance foot perfusion and may slow PAD progression in diabetes.
Cassidy et al. (2022)	Mobile & cloud-based diabetic foot ulcer detection framework.	Pilot deployment in 2 hospitals (Type 2 diabetics; Malaysia).	Enabled remote foot image uploads and AI analysis via cloud; demonstrated feasibility for patient-driven monitoring.	Showed successful multi-platform implementation (TypeScript app + cloud CNN) for DFU detection in clinical settings.	Early prototype with limited sample; highlighted potential for improving access to specialist evaluation in remote areas.
Cassidy et al. (2023)	AI-based smartphone foot ulcer detection vs clinical exam.	N = 203 foot images (UK); images from diabetic patients.	AI system achieved high sensitivity (91.6%) and specificity (88.6%), improved to 92.4% specificity with consensus approach.	Validated robust AI predictions (high inter/intra-rater reliability), supporting development of an automated ulcer monitoring app.	Promising accuracy approaching clinicians'; suggests AI could augment routine foot checks, but larger validation needed.
Chee et al. (2024)	Gait analysis via wearable accelerometers; hybrid CNN-LSTM model.	N = 40 participants (20 diabetic vs 20 non-diabetic controls; Malaysia).	Hybrid model detected diabetic vs non-diabetic gait with 91.3% accuracy.	Demonstrated a non-invasive method to screen for diabetes through gait patterns, using deep learning (CNN-LSTM).	Suggests potential for continuous diabetes monitoring with wearables; needs larger-scale validation.

Reference	Methodology / Techniques	Sample size and demographics	Key findings	Notable results / Achievements	Comments / Limitations
Chitneni et al. (2022)	Narrative analysis of fMRI in diabetic neuropathy detection.	Review of CNS activity patterns in DPN patients vs controls (study type: neuroimaging analysis).	Diabetic neuropathy patients showed increased central pain-processing activity on fMRI.	fMRI demonstrates promise as a noninvasive early detection tool for DPN, by identifying CNS activation differences.	Expensive and not routine: highlights need for further research to compare fMRI with standard peripheral neuropathy tests.
Chuesawai and Srisuwannanukorn (2023)	Cross-sectional diagnostic study; EMLA cream-induced skin wrinkling vs standard neuropathy tests.	60 diabetic patients (Thailand); compared to monofilament (SWMF) and vibration perception tests.	EMLA-induced skin wrinkling had high sensitivity (83.3%) and specificity (85.7%) for detecting peripheral neuropathy.	Proposed SSW (skin smoothness wrinkle) test as a cost-effective, non-invasive screening tool alternative to monofilament.	Suggests EMLA cream test could enable easier community screening for neuropathy, though large-scale validation is needed.
El-Nahal et al. (2024)	Microbiological study; wound swab cultures and antibiotic susceptibility.	50 diabetic foot ulcer patients (Egypt); lab analysis of isolates.	Polymicrobial infections common; P. aeruginosa was most frequent isolate. 33.3% of organisms were multi-drug resistant (MDR).	High prevalence of MDR bacteria (especially P. aeruginosa) in DFUs signals need for targeted antibiotic stewardship.	Underscores importance of early infection detection and tailored therapy; limited by single-center data.
Evangeline and Srinivasan (2024)	Thermographic image classification; custom CNN (DPN-Net) vs MobileNet/ ResNet.	Thermograms of diabetic feet (telemedicine context; India).	DPN-Net achieved ~98.5% test accuracy, outperforming pre-trained networks.	High accuracy in distinguishing healthy vs neuropathic feet with lightweight model, suitable for mobile deployment.	Validates deep learning for neuropathy screening; however, real-world performance on diverse populations remains to be tested.
Ghosal et al. (2021)	Thermal imaging analysis; image preprocessing (Canny, watershed) + CNN models.	Thermal foot image dataset (India); tested ResNet50 vs EfficientNetB0.	EfficientNetB0 achieved ~96–99% accuracy (with preprocessing), outperforming other models.	Demonstrated low-cost automated thermal screening for DFU with very high accuracy, even on raw images.	Shows potential for deployment in resource-limited settings where expert analysis is scarce.

Reference	Methodology / Techniques	Sample size and demographics	Key findings	Notable results / Achievements	Comments / Limitations
Habibu et al. (2022)	Cross-sectional survey; SF-36 quality of life questionnaire.	N = 394 diabetic patients (Nigeria); with and without foot ulcers.	Diabetic foot ulcers significantly reduced quality of life scores in physical, mental, and emotional domains.	First study quantifying QoL impact of DFU in this population – highlights drastic QoL decline associated with DFUs.	Emphasizes need for early DFU management to improve patient well-being; self-reported data may have bias.
Haryanto et al. (2024)	(Study protocol) Randomised trial design to test an ulcer recurrence risk tool (RRU tool).	Diabetic foot ulcer patients (Indonesia); sample size not reported (trial ongoing).	No published outcomes yet. Aims to evaluate if RRU tool can prevent ulcer recurrence via early detection.	First RCT targeting recurrence prediction in DFU patients. Tool expected to stratify recurrence risk for timely intervention.	Trial registered (NCT06434922); results pending publication.
Hnit et al. (2022)	Biosensor development; cerium titanate oxide-doped carbon dots for L-tyrosine detection	lab-based sensor validation	L-tyrosine detected as a biomarker for DFU infections	High sensitivity and specificity; potential for rapid DFU infection detection	Lab-based; not yet tested in clinical patient populations; requires validation in real-world DFU samples
Huang et al. (2022)	Image processing for DFU assessment; Fast R-CNN + transfer learning.	Wound images annotated by physicians (China; sample size not given).	Automated wound segmentation and classification achieved ~90% accuracy.	Demonstrated effective DFU image analysis for treatment planning, using pre-trained CNN to evaluate ulcer size and severity.	Suggests improved consistency in DFU assessment; lacking real-time testing or large dataset validation.
Kaewrat et al. (2023)	Foot geometry scanning for shoe-fit; LIDAR sensor + graph algorithms.	Lab prototype (Thailand); tested on diabetic foot molds or volunteers.	Accurate detection of foot dimensions and shape, closely imitating expert measurements.	Introduced an augmented reality foot-measuring system to prevent diabetic footwear issues.	Could help reduce ulcer risk from ill-fitting shoes; needs real-world trials on diabetic patients.

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Khandakar et al. (2022)	Thermal imaging + machine learning; k-means clustering + VGG-19 CNN.	Thermogram dataset of diabetic feet (UAE; includes healthy vs ulcer cases).	VGG-19 model classified ulcer severity with 95.1% accuracy; high sensitivity & specificity achieved.	Stacking classifier performed comparably, reinforcing that thermography can effectively grade diabetic foot complications.	Demonstrated AI can assess ulcer risk noninvasively; next step is integration into regular diabetic foot exams.
Kumsa et al. (2023)	Device innovation; foot pressure & temperature monitoring + red light therapy.	Prototype tested over 2 weeks on diabetic individuals (location not stated).	Device achieved measurement accuracy ~99% for pressure and temperature.	Integrated automated red-light therapy when thresholds exceeded, creating a dual monitoring-treatment system.	Promising for home use in low-resource settings; efficacy of therapy component needs further clinical testing.
Kunta et al. (2022)	Prospective cohort study; assessment of risk factors for diabetic foot infections	N = 120 DFU patients, tertiary care center	Identified key risk factors for DFU infection: neuropathy, poor glycemic control, PAD, prior ulceration	Provides evidence for clinical predictors of infection; useful for targeted screening	Single-centre study; moderate sample size; findings may not generalize to broader populations.
López-Moral et al. (2022)	Observational study; predictive radiographic analysis of Charcot foot deformities and risk of foot ulceration	N = 70 patients with Charcot foot; stratified by lateral or medial midfoot deformity	Radiographic parameters can predict risk of foot ulceration; lateral deformities showed higher ulceration risk	Provides specific radiographic predictors for clinical risk stratification in Charcot foot	Small sample size; single-center study; limited external generalisability.
Lei et al. (2023)	Nano-diagnostics; DNA nanomachine with roll-to-roll amplification + gold NP sensor.	Lab experiment on human serum samples (China).	Ultra-sensitive miRNA detection limit of 10 aM achieved for DFU-related biomarkers.	Established a novel electrochemical biosensor potentially useful for early DFU diagnostic markers.	Could enable early disease detection (e.g. infection) before clinical symptoms; requires validation in clinical settings.

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Madsen et al. (2022)	Nationwide registry-based cohort (Denmark); 5-year follow-up.	N = 8,394 patients with chronic leg wounds (incl. diabetic ulcers).	Wound healing incidence 236 per 1000 PY; relapse 75/1000 PY; amputation 16/1000 PY; death 100/1000 PY. Diabetes/PAD and low education were linked to poorer outcomes.	Large-scale data provided epidemiological benchmarks for wound outcomes and highlighted social inequality in amputation/mortality rates.	Chronic leg wounds in diabetics have high relapse and mortality; underscores need for targeted interventions and addressing comorbidities.
Mamdoh et al. (2023)	Microbiology of DFUs; swab culture, PCR for biofilm genes, spa typing.	N = 100 diabetic foot infection patients (Egypt).	78.1% of Staphylococcus isolates formed biofilms; high prevalence of multi-drug resistant staphylococci.	Confirmed biofilm's role in DFU severity and difficulty; identified common strain types via spa typing.	Points to need for anti-biofilm therapeutic strategies in DFU management; study limited to hospital setting.
Minty et al. (2023)	Prospective clinical study; preventative sensor-based remote monitoring for DFU	N = 120 high-risk diabetes patients	Remote sensors enabled early detection of temperature and pressure changes, reducing ulcer incidence	Demonstrated feasibility and effectiveness of sensor-based remote monitoring in clinical practice	Limited sample size; requires long-term validation; technology adoption barriers in some populations
Molines-Barroso et al. (2023)	Comparative microbiology; cultures from 3 sections of resected metatarsal heads.	N = 13 metatarsal bone samples from 12 DFU patients (Spain).	92% of bone samples had positive culture; 77% of cases showed identical bacteria in all three bone sections. Central bone segment had the highest organism count; overall 91% concordance between sections.	Demonstrated that osteomyelitis pathogens spread uniformly in bone; recommended central bone biopsy for diagnosis.	Suggests less invasive biopsy sites can represent full infection; small sample size, but informs surgical sampling strategies in diabetic osteomyelitis.
Muralidhara et al. (2022)	Deep learning on plantar thermograms; custom CNN vs AlexNet & others.	Thermogram dataset of diabetic feet (India; multiclass severity labels).	Achieved mean accuracy 0.983, sensitivity 0.968, specificity 0.989 in multi-class ulcer severity classification.	Set a new benchmark for thermogram-based DFU severity grading, with balanced performance across classes.	Demonstrated effectiveness of data augmentation to address class imbalance; could be integrated into smart health devices for diabetics.

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Murthy et al. (2024)	Medical image analysis; "Shades of Gray" preprocessing + Fast CNN classifier.	Clinical DFU images (India); infection vs non-infection labeling.	Automated infection detection reached 99.45% accuracy.	Introduced DFINET-AO segmentation and enhancements (U++ network) to achieve highly reliable DFU infection recognition.	Offers a tool for early infection diagnosis to assist clinicians; extremely high accuracy needs validation on diverse image sources.
Muthuraja et al. (2024)	Computer vision; EfficientNet (balanced width/ depth) vs AlexNet/ VGG on foot images.	N = 844 foot images (India); mixed healthy vs ulcer.	EfficientNet model attained 98.97% classification accuracy, outperforming AlexNet, GoogleNet, VGG16/19.	Demonstrated an affordable, accurate AI method for early DFU detection using optimised EfficientNet architecture.	High performance indicates potential for real-world screening apps; further work needed on app usability in clinics.
Nagaraju et al. (2023)	Advanced deep learning framework; Inception-ResNet-v2 with Sparrow Search Optimisation + stacked sparse autoencoder.	DFU image datasets (China; benchmark comparison against existing models).	The SSODL-DFUDC method outperformed prior deep learning approaches in DFU detection and classification.	Achieved superior accuracy through optimised hyperparameters and feature generation, setting a new state-of-the-art in DFU image classification.	Sophisticated model shows performance gains but may be computationally intensive; underscores the trend of hybrid optimisation in medical AI.
Naveen et al. (2023)	Novel algorithm; FO-DPSO segmentation + GLCM features + Naïve Bayes classifier.	DFU image dataset (not specified; likely hospital images, India).	Achieved 91.2% accuracy in DFU detection; sensitivity 100%, specificity ~96.7% (Naïve Bayes classifier).	The fractional-order PSO segmentation and dual-classifier approach showed high sensitivity (no missed ulcers).	Innovative segmentation improved feature extraction; specificity for one classifier was modest (~79.6%), suggesting room for refinement.
Normahani et al. (2023)	Health economics modeling; 5-year Markov model comparing PAD diagnostic tests.	Hypothetical cohort of diabetic patients with PAD suspicion (UK).	PAD-scan (handheld duplex) was most cost-effective, ICER ≈ £11.4K/QALY, and could reduce amputations by 24% vs next best test.	PAD-scan had ~79% probability of being cost-effective at £20K/QALY threshold.	Concludes PAD-scan is a cost-effective bedside test for PAD in diabetes, supporting its adoption; analysis assumes UK cost structure.

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Omar et al. (2023)	Cross-sectional biomarker study; measured PCT, CRP, TWC in DFU patients.	3 groups: healthy controls, non-infected DFU, infected DFU (Malaysia).	Procalcitonin (PCT) levels significantly higher in infected DFUs than non-infected; PCT sensitivity was moderate (63.6%) for early infection detection.	PCT identified infected ulcers but with limited sensitivity, suggesting it can support, not replace, clinical diagnosis.	PCT is a useful adjunct marker but not sufficiently sensitive alone for early DFU infection; combining markers could improve diagnostic accuracy.
Pan et al. (2022)	Experimental therapeutics; Wuguchong (insect) peptide enzymatic digest + network pharmacology.	Lab assays + bioinformatics (China); tested on cell models of wound healing.	Identified pro-angiogenic compounds from Wuguchong that significantly accelerated wound healing in vitro.	Provided scientific insight into a traditional medicine, showing enhanced angiogenesis and wound closure from the peptide compounds.	Bridges ethnomedicine and modern science; suggests potential new DFU treatments but so far tested only in lab models.
Pany et al. (2022)	Microbiology; PCR detection of PVL gene in S. aureus from DFU samples.	Tissue and blood samples from DFU patients (India; tertiary hospital).	Prevalence of PVL toxin gene was higher in MSSA strains than MRSA in diabetic ulcers. High antibiotic resistance patterns observed.	Revealed that community-associated virulence (PVL+) exists even in methicillin-susceptible strains, underscoring the threat beyond MRSA.	Calls for tailored antimicrobial therapy based on virulence profiling; single-center data but important for antibiotic policy in DFU.
Qi et al. (2024)	Clinical cohort + LAMP diagnostic development for MRSA.	N = 522 hospitalized DFU patients (China) for culture; new LAMP assay evaluated on MRSA isolates.	MRSA was present in 33.7% of DFI patients; MRSA-infected patients had higher osteomyelitis (46.9%) and amputation/disability rates (40.8%). Developed a LAMP test identifying predominant MRSA subtype in ~1.5 h with 100% sensitivity, 77.8% specificity.	Highlighted the heavy burden of MRSA in DFUs and introduced a rapid genetic screening for MRSA (SCCmec type II) to enable quick isolation and treatment.	Confirms MRSA infections lead to worse outcomes in DFU; rapid point-of-care MRSA detection can improve infection control (specificity moderate but sensitivity high).

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Qin et al. (2022)	Large cross-sectional study; thermography + plantar pressure + mixed model analysis.	N = 1,007 diabetic clinic patients in Japan (foot thermograph and pressure data).	18.5% of callused feet had a "hotspot" (local temp rise). More calluses (aOR 1.54), higher static forefoot peak pressure (aOR 1.008) were significantly associated with inflammatory hotspots.	Identified plantar pressure (SFPPP) as a useful predictor of callus inflammation risk. This non-invasive indicator can inform targeted offloading.	Suggests integrating thermography and pressure measurement in routine foot exams to pre-empt ulcers; study is retrospective with inherent limitations.
Rai et al. (2022)	Infrared thermal imaging for DFU risk; segmented foot regions, temperature threshold analysis.	50 diabetic patients (India); compared IR findings with ML classification outcomes.	Infrared scanning effectively identified areas at ulcer risk via >2.2°C temperature differences, with simpler implementation than complex ML.	Provided a non-invasive early warning method for foot ulcers that is straightforward to interpret, advocating IR cameras as a practical clinic tool.	While not as automated as ML, IR imaging is cost-effective and user-friendly; recommended as first-line screening especially where ML infrastructure is lacking.
Rossboth et al. (2022)	Retrospective analysis of real-world diabetic foot data (specialised center).	N = 3,002 diabetic patients (Austria); long-term follow-up for foot complications.	Observed 61 diabetic foot complications. Cox regression showed older age at diabetes diagnosis, longer diabetes duration, and presence of PAD significantly predicted foot complications.	Real-world data highlighted patient factors contributing to foot complication risk, reinforcing early screening in elderly diabetics.	Provided "lessons learned" from a large dataset: calls for targeting high-risk groups (e.g. seniors, those with comorbid PAD) to reduce ulcers and amputations.
Sabaghan et al. (2023)	Cross-sectional prevalence study; multistage sampling + clinical exam.	N = 453 type 2 diabetes patients (Iran); screened for DPN signs.	Diabetic peripheral neuropathy prevalence was 26.2%; additionally, 41.3% of patients were classified as high risk for foot ulcer. Older age, longer diabetes duration, high HbA1c, hyperlipidemia, and hypertension were significant risk factors for DPN.	Exposed a large undiagnosed burden of neuropathy (over 40% at ulcer-risk) in the diabetic population.	Recommends annual neuropathy screening and aggressive management of modifiable risk factors to prevent foot ulcers; single-center data but with robust sampling.

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Saltoglu et al. (2023)	Multicenter prospective study; collected pathogen data & outcomes, multivariate analysis.	N = 284 DFI patients (Turkey, 5 centers; ~68% male, mean age ~60).	247 microorganisms isolated (avg ~1.3 per patient); most common were S. aureus (14.6%) and E. coli (13.0%). Inappropriate initial antibiotics led to higher reinfection (especially Klebsiella-related). Polymicrobial infection and vancomycin use were independent predictors of reinfection/death; vascular insufficiency, high CRP, and carbapenem use predicted major amputation.	Provided real-world evidence that improper empirical antibiotic choices worsen outcomes (reinfections, amputations) in DFIs. Supports using narrower-spectrum antibiotics guided by local resistance patterns to improve healing.	Underscores need for culture-driven therapy: high MDR rates (e.g. 19% MRSA, 69.6% MR-CoNS, 18% MDR Pseudomonas) demand prudent antibiotic selection.
Sarmun et al. (2024)	Deep learning ensemble for DFU detection; YOLOv8m + Faster R-CNN with NMS fusion.	Compiled DFU image dataset (Malaysia); external validation on separate set.	Ensemble model achieved 86.4% mean Average Precision for ulcer localization. Demonstrated robust performance on an external validation dataset, outperforming single models.	By using soft-NMS and weighted box fusion, the model improved detection accuracy and reduced false negatives in identifying foot ulcers.	Enhances reliability of automated DFU diagnosis; however, ensemble complexity may challenge deployment on low-power devices.
Sharma et al. (2023)	Thermal imaging & ML; region-wise (forefoot/midfoot/ hindfoot) severity classification using logistic regression, SVM, CNNs.	N = 104 subjects (diabetic patients with varying ulcer severity; Thailand).	Developed a new plantar thermal dataset; both classical ML and CNN (EfficientNetB1, VGG-16) effectively classified ulcer severity by region. Region-specific temperature patterns helped target interventions to high-risk foot areas.	Introduced region-based analysis, which improved classification granularity – enabling precise identification of which foot area is at risk and needs offloading.	Validated concept of segmenting foot for analysis; combining ML and thermal imaging could tailor preventative care, though data were limited to a single center.

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Shobana et al. (2023)	Electrochemical biosensor development; L-tyrosine detection via modified GCE electrode.	Lab study (India); tested sensor on simulated infected wound fluid.	Achieved a low L-tyrosine detection limit of 26 nM, indicating high sensitivity.	The cerium-titanate-doped carbon dot electrode reliably detected a biomarker of wound infection, potentially signaling early DFU infections.	Offers a rapid, sensitive method to detect infection metabolites; needs clinical validation to correlate tyrosine levels with infection onset.
Spaide et al. (2023)	Infrared thermal imaging vs deep learning comparison for early ulcer detection.	Small cohort of diabetic patients (USA); IR images analysed in MATLAB.	Infrared imaging with a 2.2°C temperature threshold identified ulcer-risk areas, proving to be a feasible, straightforward alternative to complex DL methods.	Showed that a simple thermal approach can highlight hotspots without requiring advanced AI, making it accessible for widespread use.	Thermal imaging is user-friendly but might be less precise than AI; nonetheless, it provides immediate visual cues for clinicians and patients.
Tantigegn et al. (2023)	Retrospective follow-up study (Kaplan–Meier + Cox regression) on neuropathy onset.	N = 669 adults with diabetes (Ethiopia); median follow-up ~5 years.	Time to diabetic neuropathy was significantly shorter in patients >60 years old, and those with diabetic retinopathy, anemia, hypertension, or FBS >200 mg/dL.	Identified key predictors for earlier neuropathy onset, enabling risk stratification – e.g. older age doubled neuropathy risk.	Stresses early intervention in high-risk groups (elderly, co-morbid conditions) to delay neuropathy; suggests integrating these risk factors in routine assessments.
Tegegne & Wubante (2022)	Cross-sectional observational study; diabetic foot ulcer prevalence and risk factors assessment	N = 420 type 2 diabetes patients, Ethiopia	Prevalence of DFU ~14%; risk factors include neuropathy, poor glycemic control, and longer diabetes duration	Provides population-level risk assessment in Ethiopian cohort; identifies modifiable risk factors	Cross-sectional design cannot establish causality; single-center study limits generalizability
Verma (2024)	Thermal image pre-processing (Canny & watershed) + CNNs (ResNet50, EfficientNetB0).	N = 1,055 foot thermograms (India); comparisons on raw vs pre-processed images.	Ulcer detection accuracy improved from ~89% (raw) to 99.4% after image pre-processing with EfficientNetB0.	Demonstrated that proper image pre-processing dramatically boosts deep learning performance for DFU detection.	Validated a practical pipeline (edge enhancement + CNN) for real-world applications, achieving near-perfect accuracy in controlled conditions.

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Viswanathan et al. (2024)	Nationwide cross-sectional campaign; 3-min foot exam + questionnaire (India).	N = 33,259 people with diabetes across India; community screening by trained staff.	25.2% of participants had "high-risk" feet (neuropathy, deformity, or past ulcer). High-risk status was significantly associated with foot deformities, heel fissures, calluses, and longer diabetes duration.	Largest survey of diabetic foot risk in India, revealing a substantial burden of high-risk feet and gaps in primary foot care.	Recommends regular foot screening at primary care level nationwide; study underscores urgent need for podiatric services in diabetes care.
Wang et al. (2023)	Microbiome and virulence analysis; nasal swabs, strain typing (ST7 vs ST59).	N = 36 diabetic patients vs 30 controls (mice model for colonization included; China).	Diabetic patients (especially with poor glycemic control) were predominantly colonized by highly virulent S. aureus ST7 strains, which showed greater biofilm formation and resistance to antimicrobial peptides than ST59.	Demonstrated that hyperglycemia via the SaeRS two-component system favors colonization by more virulent S. aureus strains. This may partly explain increased infection severity in diabetics.	Stresses importance of screening and decolonizing nasal S. aureus in diabetic patients with high FBG to prevent invasive infections.
Wu et al. (2024)	Deep learning model (YOLOv5 with CBAM, BiFPN, GhostC3, etc.) for lower extremity artery stenosis (LEAS) detection.	3D reconstructed vessel images from diabetic foot patients (China); model compared against 5 others.	Enhanced YOLOv5 model achieved 85.4% mAP and 74.6 FPS in detecting arterial stenoses, outperforming all comparison models.	The model runs in real-time (>70 FPS) while maintaining high precision, showing potential for fast screening of PAD-related foot ischemia.	Could aid rapid point-of-care PAD diagnostics in diabetic clinics, allowing immediate treatment planning; requires clinical validation on actual angiography images.
Yakout & Abdelwahab (2022)	Microbiological survey during COVID-19; wound swabs, pathogen ID & biofilm gene analysis.	N = 100 diabetic foot infection cases (Egypt, 2020–2021).	High prevalence of biofilm-forming Pseudomonas aeruginosa identified in DFUs, alongside other common pathogens.	P. aeruginosa emerged as the dominant DFI pathogen in this cohort, often with biofilm genes, suggesting it thrived during pandemic conditions.	Indicates need for biofilm-disrupting treatments and vigilance for P. aeruginosa in DFUs, especially when healthcare access is disrupted (as during COVID-19).

Reference	Methodology / Techniques	Sample size and demographics	Key findings	Notable results / Achievements	Comments / Limitations
Yan et al. (2024)	Comparative microbiome study; nasal microbiota analysis in diabetic vs non-diabetic (extension of Wang 2023 findings).	Diabetic patients with chronic hyperglycemia vs non-diabetics (China); included in vivo nasal colonization models.	Chronic hyperglycemia promoted nasal colonization by virulent S. aureus (SaeRS-regulated) strains, which showed enhanced biofilm formation and resistance.	Reinforced that glycemic environment drives pathogenic colonization: hyperglycemia can tip the balance toward more aggressive bacterial strains.	Supports tight glucose control as part of infection prevention strategy in diabetics; study provides a mechanistic link between diabetes and altered pathogen behavior.
Yogapriya et al. (2022)	Convolutional neural network (22-layer "DFINET") for DFU infection detection.	DFU clinical image set (China); augmented for infection vs clean classification.	DFINET achieved 91.98% accuracy (MCC = 0.84) in identifying infected ulcers vs non-infected.	Introduced parallel convolution layers and dropout normalization to improve infection recognition in images.	Validates AI assistance for clinicians in diagnosing DFU infections quickly; high MCC indicates robust performance, though real-world variability (different cameras, lighting) needs further testing.
Zhao et al. (2023)	Hyperspectral imaging (HSI) study; measured oxygen saturation in DFU tissue.	N = 20 DFU patients (USA); 10 healing vs 10 non-healing ulcers monitored.	Healing ulcers showed higher oxygen saturation (54–64%) vs non-healing (32–48%) on HSI.	Demonstrated HSI can non-invasively differentiate healing potential of ulcers by visualizing perfusion levels.	Promising tool for predicting wound healing outcomes and guiding treatment intensity; needs larger trials but could reduce reliance on invasive tissue perfusion measurements.

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Ziegler et al. (2024)	Cross-sectional survey of podiatrists; online questionnaire about DPN practices.	N = 125 podiatrists (Germany); asked about screening frequency and findings.	Most podiatrists regularly detected previously undiagnosed diabetic polyneuropathy (DPN) and some foot ulcers during routine care. However, screening methods and frequency varied.	Highlights the pivotal role of podiatrists in early DPN and ulcer detection – many cases are caught in podiatry clinics rather than diabetes clinics.	Recommends standardizing DPN screening protocols in podiatry practice and better integrating podiatrists into diabetes care teams to improve outcomes.

Note.
α = Cronbach's alpha; aM = Attomolar; aOR = Adjusted Odds Ratio; AI = Artificial Intelligence; ANN = Artificial Neural Network; BiFPN = Bidirectional Feature Pyramid Network; CBAM = Convolutional Block Attention Module; CNN = Convolutional Neural Network; CNN–LSTM = Convolutional Neural Network–Long Short-Term Memory; CNS = Central Nervous System; CRP = C-Reactive Protein; DFU = Diabetic Foot Ulcer; DFI = Diabetic Foot Infection; DFINET = Diabetic Foot Infection Network; DFINET-AO = Diabetic Foot Infection Network – Attention Optimized; DL = Deep Learning; DNA = Deoxyribonucleic Acid; DPN = Diabetic Peripheral Neuropathy; DPN-Net = Diabetic Peripheral Neuropathy Network (custom CNN); EMLA = Eutectic Mixture of Local Anesthetics; FBG = Fasting Blood Glucose; FBS = Fasting Blood Sugar; fMRI = Functional Magnetic Resonance Imaging; FO-DPSO = Fractional-Order Darwinian Particle Swarm Optimization; FPS = Frames Per Second; GCE = Glassy Carbon Electrode; GLCM = Gray-Level Co-occurrence Matrix; GLP-1 = Glucagon-Like Peptide-1; HbA1c = Hemoglobin A1c; HIS = Hyperspectral Imaging; ICER = Incremental Cost-Effectiveness Ratio; ID = Identification; I-CVI = Item-Level Content Validity Index; IR = Infrared; LAMP = Loop-Mediated Isothermal Amplification; LEAS = Lower Extremity Artery Stenosis; LIDAR = Light Detection and Ranging; M-DFEET = Mobile Diabetic Foot Evaluation and Education Tool; mAP = Mean Average Precision; MATLAB = Matrix Laboratory (software); MCC = Matthews Correlation Coefficient; MDR = Multidrug-Resistant; miRNA = MicroRNA; ML = Machine Learning; MR-CoNS = Methicillin-Resistant Coagulase-Negative *Staphylococci*; MRSA = Methicillin-Resistant *Staphylococcus aureus*; MSSA = Methicillin-Sensitive *Staphylococcus aureus*; NMS = Non-Maximum Suppression; NP = Nanoparticle; PAD = Peripheral Artery Disease; PCR = Polymerase Chain Reaction; PCT = Procalcitonin; PVL = Panton–Valentine Leukocidin; PY = Person-Year; QALY = Quality-Adjusted Life Year; QoL = Quality of Life; R-CNN = Region-Based Convolutional Neural Network; RCT = Randomized Controlled Trial; ResNet = Residual Network; RRU = Recurrent Risk of Ulcer; SCCmec = Staphylococcal Cassette Chromosome *mec*; SFPPP = Static Forefoot Peak Plantar Pressure; SSODL-DFUDC = Sparrow Search Optimization-Based Deep Learning for Diabetic Foot Ulcer Detection and Classification; SSW = Skin Smoothness Wrinkle; SVM = Support Vector Machine; SWMF = Semmes–Weinstein Monofilament; T2DM = Type 2 Diabetes Mellitus; $TcPO_2$ = Transcutaneous Partial Pressure of Oxygen; TWC = Total White Cell Count; U++Net = Nested U-Net++ Convolutional Neural Network; UAE = United Arab Emirates; UK = United Kingdom; USA = United States of America; VGG-19 = Visual Geometry Group 19-Layer; YOLOv5 = You Only Look Once version 5 (object detection model)