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Review

Application of artificial intelligence and new technologies in the diagnosis of diabetic foot

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ABSTRACT

Diabetic foot syndrome (DFS), particularly diabetic foot ulcers (DFU), represents a severe complication of diabetes leading to infection and amputation. Early detection is challenging due to complex pathophysiology and conventional diagnostic limitations. Advances in artificial intelligence (AI), deep learning, and wearable technologies offer new opportunities for improved diagnosis and monitoring. The aim of this review is to analyse current applications of AI, deep learning models, and sensor-based technologies in the diagnosis, classification, and prevention of DFS. A narrative review was conducted using PubMed, ScienceDirect, and Google Scholar (2020–2025). Studies employing deep learning for DFU detection and wearable technologies for monitoring were evaluated for clinical applicability. Deep learning architectures, including convolutional neural networks (CNNs), hybrid models, and transformers, achieved high diagnostic performance, frequently exceeding 99% accuracy in DFU classification. Models integrating segmentation enabled precise lesion localization. Explainable AI (XAI) approaches improved clinical trust, while thermographic imaging showed promise for non-invasive detection. Wearable technologies, such as smart socks and pressure-sensing insoles, enabled continuous physiological monitoring, supporting personalized prevention strategies. AI and emerging technologies significantly enhance diagnostic capabilities in DFS. Deep learning models demonstrate excellent performance, while sensor-based systems extend monitoring beyond clinical settings. However, widespread implementation requires further prospective validation and standardized protocols. AI solutions should be viewed as decision-support tools that complement clinical expertise.

KEYWORDS

diabetic foot syndrome, diabetic foot ulcer, artificial intelligence, deep learning, explainable AI, medical image analysis, wearable sensors, thermography, clinical decision support, digital health

Introduction

Diabetes mellitus (Latin: *diabetes mellitus*) is a chronic, progressive metabolic disease characterized by disturbances in glucose homeostasis resulting from defects in insulin secretion, insulin action, or, frequently, both mechanisms simultaneously. Over recent decades, a rapid increase in the global incidence of diabetes has been observed, making it one of the most serious public health challenges of the 21st century [1,2,3,4]. New data published by the World Health Organization (WHO) indicate that in 2014 an estimated 422 million adults worldwide were living with diabetes, compared with 108 million in 1980. According to WHO projections, by 2030 diabetes will rank as the seventh leading cause of death [2,5]. The rising incidence correlates with

multiple risk factors, including population aging, urbanization, lifestyle changes, sedentary behaviour, unhealthy diet, and the increasing prevalence of overweight and obesity [3,6].

In its early stages, the disease is often asymptomatic, which significantly delays diagnosis and initiation of treatment. Uncontrolled hyperglycemia contributes to the development of chronic microvascular and macrovascular complications, including diabetic nephropathy, retinopathy, peripheral neuropathy, cardiovascular diseases, stroke, and diabetic foot syndrome, which in advanced cases leads to lower limb amputations [7,8].

Diabetes has a substantial impact on patients' quality and length of life. Individuals with poor glycemic control are at a higher risk of premature mortality [9,10,11]. At the same time, the disease imposes a significant burden on healthcare systems, mainly due to the costs associated with managing complications, hospitalizations, pharmacotherapy, and loss of work productivity [12]. Therefore, a holistic approach is essential, encompassing early diagnosis (with particular emphasis on high-risk groups), intensive diabetes education, promotion of a healthy lifestyle, primary and secondary prevention, and individualized pharmacotherapy with regular glycemic monitoring. Interdisciplinary care for patients with diabetes should involve not only a diabetologist, but also a dietitian, diabetes nurse educator, psychologist, and specialists managing comorbid conditions [13].

Among patients with complications, more than half (57%) report satisfaction with their quality of life, whereas only 23% are satisfied with their health status. The largest proportion of respondents (47%) are neither satisfied nor dissatisfied with their health. Individuals who are very dissatisfied with their health appear exclusively in the group with diabetic complications [14].

Diabetes is not only an individual but also a societal problem, requiring coordinated systemic actions, including health policy measures, preventive strategies, screening programs, and investments in technologies supporting self-monitoring and disease management. In this context, increasing attention is being paid to the use of artificial intelligence methods and devices for continuous monitoring of foot parameters in patients, which may enable earlier detection of pathological changes and intervention before advanced complications develop [15,16].

Statistics

On a global scale, diabetes represents a growing public health problem whose scale is steadily increasing. According to data from the International Diabetes Federation (IDF) Diabetes Atlas, in

2021 as many as 537 million adults were living with diabetes worldwide, which constitutes a significant increase compared with earlier historical assessments. Projections from international epidemiological models indicate that by 2030 the global number of patients with diabetes may reach as many as 643 million, and escalate further to 783 million by 2045. It is estimated that approximately 45% of diabetes cases globally remain completely undiagnosed, which further increases the true magnitude of the problem. These data clearly demonstrate the need to intensify preventive, educational, and diagnostic measures across the entire population [1].

In a prospective study, outcomes among patients presenting with infected diabetes-related foot ulcers (DFU) showed healing in only 46% of cases (with recurrence in 10% of those), while 15% of patients died and 17% required lower limb amputation [17]. Diabetic foot syndrome is a condition with a complex etiology, involving peripheral neuropathy, immune dysfunction, and vascular insufficiency, which frequently lead to ulceration, infection, and amputation [18]. The majority of foot ulcers in individuals with diabetes arise as a result of repetitive trauma to an insensate foot due to loss of protective sensation from neuropathy, most commonly located on the plantar surface [17]. Typical clinical features of the neuropathic foot include absence of pain or significant pain reduction, sensory disturbances (particularly of vibration and touch), normal warmth and pink coloration of the skin, as well as palpable pulses in the dorsalis pedis and posterior tibial arteries [19].

Theoretical foundations and new technologies in the diagnosis of DFU

Deep learning is an advanced artificial intelligence method capable of independently analysing very large datasets by identifying complex patterns and relationships. It relies on the so-called backpropagation algorithm, which enables the system to learn by gradually correcting its own errors during data analysis. In recent years, these techniques have been widely applied in medicine, particularly in the analysis of clinical images. Convolutional neural networks (CNNs) have proven especially effective in recognizing structures in images, including the assessment of photographs of the feet of patients with diabetes, computed tomography scans, X-rays, and dermoscopic images. Recurrent neural networks (RNNs), in turn, are used for the analysis of sequential data, such as glycemic monitoring results, ECG (electrocardiogram) recordings, or signals from sensors [20].

Unlike classical machine learning, deep learning does not require manual definition of features relevant for disease recognition. Instead, the network learns these features autonomously during data processing. However, a key factor determining model performance is the quality and diversity

of the training data. Even the most advanced network architecture cannot compensate for an insufficient quantity or poor quality of data.

An important limitation of deep learning methods in clinical applications is the phenomenon of overfitting. In this case, a model may perform very well on the data on which it was trained but show reduced performance in real-world practice when analysing new patient cases [21]. Therefore, appropriate data preparation, model validation, and testing under real clinical conditions are essential.

Although the development of artificial intelligence algorithms opens new possibilities for clinical data analysis, an essential complement to these solutions is provided by sensor technologies and wearable devices that enable real-time data acquisition. Their integration with AI systems allows not only for analysis but also for early detection of alarming changes, even before clinical symptoms appear. The subsequent section of this work presents selected sensor technologies and discusses their application in clinical practice [22].

Methods

Search strategy and data sources

To ensure methodological transparency and reproducibility, a systematic literature screening was performed across three major international databases: PubMed, ScienceDirect, and Google Scholar. The database query was executed on April 10, 2025. The search string was structured using Boolean operators to combine specific keywords relating to artificial intelligence architectures and clinical diabetic foot applications: ("deep learning" OR "artificial intelligence") AND ("diabetic foot" OR "diabetic foot ulcer" OR "DFU") AND ("smart socks" OR "wearable sensors" OR "foot pressure monitoring").

Inclusion and exclusion criteria

The selection of literature followed strict boundaries to distill high-quality, relevant scientific evidence:

- Inclusion criteria: (1) Original research articles and comprehensive technical studies published in peer-reviewed journals within the last five years (2020–2025); (2) Research utilizing advanced deep learning frameworks (e.g., Convolutional Neural Networks, Transformer architectures, Object Detection models, or Ensemble configurations) as the core analytical methodology; (3) Research investigating computerized DFU localization,

multi-class classification, segmentation, or predictive monitoring using wearable technology; (4) Publications written in English.

- Exclusion criteria: (1) Preprints, abstracts, editorials, and non-peer-reviewed conference proceedings; (2) Studies lacking explicit quantitative validation protocols or missing key evaluation metrics, such as accuracy, precision, recall, F1-score, or Area Under the ROC Curve (AUC); (3) Papers focusing solely on classic machine learning models or statistical regressions without modern neural network architectures.

Data extraction and study evaluation

The initial search results were exported to reference management software to remove duplicates. Titles and abstracts were independently screened by the authors to filter out irrelevant records, followed by a meticulous full-text appraisal of the remaining publications. For each eligible study, a structured data extraction protocol was applied to collect and evaluate the following characteristics:

1. Dataset specifications: Data source (e.g., public benchmarks like DFUC2020, DFUC2021, or private clinical cohorts), overall sample size, and the utilization of data augmentation techniques.
2. Algorithmic framework: The specific architecture variants deployed (e.g., YOLOv5s, ResNet101, Swin Transformer, EfficientNet-B1, U++Net).
3. Performance metrics: Quantitative outcomes, including classification accuracy, mean Average Precision (mAP) for localization, F1-score, and AUC (Area Under the ROC Curve) values.
4. Clinical modality: The use of conventional RGB photography, thermal imaging (thermography), or continuous sensor networks.

The extracted data were synthesized and critically appraised, focusing on common structural limitations such as dataset biases, risks of overfitting, and practical challenges to real-world clinical adoption, which are detailed in the subsequent sections of this review.

Results

DFU lesion localization and object detection techniques

Automatic localization of diabetic foot ulcers (DFU) within clinical photographs represents a critical preliminary phase in digital workflows, particularly for automated medical documentation and telemedicine frameworks. Rather than evaluating the entire image, modern computer vision systems employ object detection networks to act as an automated diagnostic tool, dynamically

identifying and bounding pathological regions while filtering out complex backgrounds or clinical artifacts. A prominent implementation of this approach is observed in the multi-functional DFUCare diagnostic platform. Within its modular pipeline, the system utilizes a fine-tuned YOLOv5s (You Only Look Once) architecture. Serving as the system's initial visual processing layer, YOLOv5s automatically detects and isolates ulcerated regions from photographic datasets (such as DFUC2020). To support downstream clinical metrics, the platform integrates these bounding regions with ArUco markers and the OpenCV library, enabling automated physical wound measurements with an accuracy threshold within a few millimeters (mean discrepancy ≤ 0.3 cm) [23].

However, reliance on a single object detection network can limit diagnostic robustness when encountering atypical ulcer morphologies, varied lighting conditions, or low-resolution inputs. To mitigate these real-world constraints, recent investigations have moved toward ensemble learning strategies. By combining complementary network architectures, ensemble systems achieve superior localization reliability. Evaluation of diverse model combinations demonstrates that the integration of YOLOv8m and Faster R-CNN - Faster Region-based Convolutional Neural Network (FRCNN-ResNet101) utilizing a Weighted Boxes Fusion (WBF) strategy yields the highest localization efficacy, achieving a mean Average Precision (mAP@0.5) of 0.864 and an F1-score of 0.806 (Table I) [24].

Table I. Clinical evaluation and localization accuracy of ensemble deep learning models

Model Combination	Ensemble Approach (How models cooperate)	Wound Localization Accuracy (Sensitivity)	Clinical Meaning & Practical Utility for the Medical Team
YOLOv8m + Faster R-CNN	**Weighted Boxes Fusion (WBF):** Models balance each other's predictions to find the most accurate wound borders.	**86.4%** *(Highest performance)*	**Best choice for clinical practice.** Safely identifies atypical ulcer shapes, asymmetric margins, and wounds photographed under poor or uneven lighting.
YOLOv8x + Faster R-CNN	**Weighted Boxes Fusion (WBF):** Heavy, complex model cooperation.	**85.9%**	Very high sensitivity, but requires significant computing power. Not optimal for local or battery-powered mobile devices.
YOLOv8m + YOLOv8x + Faster R-CNN	**Non-Maximum Suppression (NMS):** Models vote on the single best bounding box by eliminating overlapping guesses.	**84.5%**	Performs better than any single model alone, but adding the third network introduces unnecessary system lag without a clinical benefit.

YOLOv7x + YOLOv8x + Faster R-CNN	**Soft-NMS:** Gradually lowers the scores of overlapping wound guesses rather than deleting them instantly.	**82.6%**	**Reduced performance.** The increased complexity causes the system to miss subtle edge boundaries of early ulcers.
YOLOv8m + EfficientDet-D1	**Weighted Boxes Fusion (WBF):** Cooperation between a rapid detector and a lightweight framework.	**81.2%**	**No significant improvement.** Routinely confused by clinical artifacts such as background bedsheets, medical rulers, or non-ulcerated skin discoloration.

Crucially, while these object detection and ensemble pipelines demonstrate high precision in spatial boundary localization, they operate purely as structural detectors. They do not classify underlying clinical complications, such as infection or ischemia, which are paramount for comprehensive therapeutic choice. Consequently, standalone localization networks must be coupled with qualitative classification frameworks to provide sufficient clinical decision support.

Qualitative feature classification: Ischemia and infection discrimination

Beyond spatial localization, the secondary modular layer of the DFUCare platform, alongside standalone deep learning architectures, evaluates qualitative tissue pathology—primarily differentiating between ischemia and infection. Because these secondary complications directly influence amputation risk and patient mortality, their rapid identification is crucial. Deep convolutional neural network (CNN) architectures have been extensively evaluated for binary and multi-class DFU feature discrimination. The DFUCare platform and standalone deep learning architectures have leveraged deep residual frameworks, specifically ResNet50 and the deeper ResNet101, utilizing transfer learning and extensive data augmentation on datasets such as DFUC2020. As summarized in comparative benchmarks (Table II), deep architectures demonstrate outstanding capabilities in identifying ischemia [23,25].

Table II. Comparative classification performance of ResNet architectures

Framework Source	Classification Task	Evaluated Architecture	Accuracy (%)	AUC (%)	MCC (%)
DFUCare [23]	Ischemia (Binary)	ResNet50	99.49	99.96	98.99
DFUCare [23]	Infection (Binary)	ResNet50	84.76	94.16	75.57
Deep Learning Approach [25]	Ischemia (Binary)	ResNet101	99.65	99.59	99.29
Deep Learning Approach [25]	Infection (Binary)	ResNet101	84.12	93.05	74.62

The comparative data reveals a distinct discrepancy in model performance across tasks. While both ResNet50 and ResNet101 exceed 99% accuracy in isolating ischemic features due to visible textural and vascular skin alterations, infection recognition remains noticeably suboptimal, hovering around 84–85% across both frameworks. This performance drop underscores a critical clinical limitation: visual RGB image analysis alone lacks the diagnostic sensitivity required to reliably differentiate subtle bacterial and inflammatory skin metrics from standard granulated wound tissue. To bridge this gap, modern diagnostic pipelines require the integration of non-visual modalities (such as laboratory biomarkers or thermography) or the application of highly advanced multi-scale neural architectures. A major architectural shift involves moving from standard CNNs toward multi-class attention networks. For instance, frameworks leveraging the EfficientNet family (particularly the EfficientNet-B1 variant) optimize width, depth, and resolution scaling simultaneously. This allows the model to process simultaneous multi-class evaluations with lowered hardware requirements, making it viable for edge computing devices or bedside screenings [26,27].

Concurrently, the integration of the Swin Transformer coupled with an Efficient Multi-scale Attention-Driven Network (EMADN) shifts the analytical scope. Unlike standard CNNs that evaluate localized pixels sequentially, the Swin Transformer utilizes shift-window self-attention mechanisms to process images at both macro- and micro-anatomical scales. This enables the model to address highly complex multi-class tasks, such as classifying images simultaneously into four distinct clinical cohorts: infection, ischemia, their dangerous co-existence, or normal tissue. However, this increased task complexity directly affects nominal performance metrics. The Swin+EMADN architecture achieves an overall accuracy of 78.79% and an F1-score of 80%. While significantly lower than the near-perfect metrics reported for simpler binary models, this multi-class holistic classification offers a more realistic approximation of true clinical scenarios where pathologies rarely present in isolation [28].

Hybrid frameworks: Integrating automated segmentation with lightweight classification

To combat the dense artifacts, varying background noise, and peripheral skin variations found in routine clinical settings, top-tier diagnostic frameworks have evolved from standalone classification pipelines into hybrid, multi-stage systems. These hybrid models first apply dense segmentation to isolate pure pathological tissue before running classification algorithms, thereby preventing the network from learning false correlations from background elements. A state-of-the-art representation of this dual-stage framework utilizes an advanced U++Net architecture for initial tissue segmentation, followed by a customized Pre-trained Fast Convolutional Neural Network (PFCNN) for rapid qualitative classification (Figure 1).

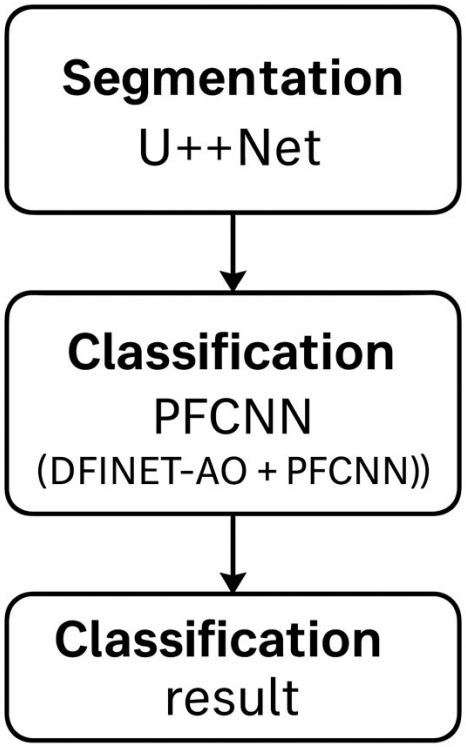

Fig. 1. Schematic representation of the hybrid dual-stage classification framework

In this pipeline, the U++Net architecture—an advanced nested extension of standard medical U-Net models—utilizes histogram analysis and fuzzy logic to map and isolate the precise boundaries of diseased tissue. By applying this dynamic background masking, the system ensures that the subsequent classifier focuses exclusively on the Region of Interest (ROI). The second stage incorporates the lightweight PFCNN model enhanced by a DFINET-AO module designed for deep feature extraction. Instead of relying on superficial visual attributes like macroscopic color, the DFINET-AO layer extracts complex micro-textural signatures indicating deep-seated tissue inflammation, exudate levels, and irregular margins. Trained on an exceptionally large, augmented dataset of 29,450 examples, this dual-stage framework achieves a remarkable clinical classification accuracy of 99.45% in infection detection. Crucially, because the underlying PFCNN is mathematically streamlined, it maintains an incredibly low computational footprint. This unique synergy solves a major dilemma in digital health: it delivers maximum scientific performance while remaining lightweight enough to be deployed directly onto low-resource hardware, such as mobile smartphones or local primary care tablets, facilitating immediate point-of-care diagnostics [29].

Explainable AI and autonomous binary classification metrics

While multi-class and hybrid models extend diagnostic breadth, standalone binary classification models—engineered to distinguish strictly between healthy skin and active DFU pathologies—remain the benchmark for high-throughput screening applications. However, as deep learning systems scale in accuracy, they increasingly function as uninterpretable "black boxes," presenting

a substantial barrier to clinical adoption and regulatory approval. To bridge the gap between mathematical accuracy and clinical trust, recent state-of-the-art frameworks have integrated Explainable AI (XAI) mechanisms directly into their classification layers. A prominent architecture in this domain is the XAI-FusionNet model, which features a triple-model fusion strategy integrating three pre-trained convolutional neural networks: DenseNet201, VGG19, and NASNetMobile. Designed with a primary focus on resource-constrained clinical settings, FusionNet minimizes parameter counts to allow rapid deployment on portable edge devices or regional hospital infrastructure. Rather than outputting a raw probabilistic prediction, the model integrates SHAP (Shapley Additive explanations), LIME (Local Interpretable Model-agnostic Explanations), and Grad-CAM (Gradient-weighted Class Activation Mapping). These tools isolate and visually emphasize the precise pixel regions and textural anomalies that dictated the algorithm's final decision, transforming a standard binary output into an auditable diagnostic report [30].

In direct performance benchmarks, FusionNet achieves a binary classification accuracy of 99.05%. This performance is closely matched by optimized, autonomous pipelines such as the SSODL-DFUDC model, which utilizes an Inception-ResNet-v2 feature extractor optimized via a Social Spider Optimization (SSO) algorithm and classified through Stacked Sparse Autoencoders (SSAE), yielding an overall performance metric of 99.29% [31].

To provide the comprehensive critical synthesis requested by clinical reviewers, the core capabilities, architectural strengths, and severe laboratory-to-clinical limitations of these dominant computer vision modalities are systematically contrasted in Table III.

Table III. Comprehensive comparative analysis of dominant DFU computer vision architectures

Architecture / Model Framework	Core Clinical Task	Peak Reported Performance	Key Architectural Strengths	Crucial Limitations & Deployment Barriers
ResNet50 / ResNet101 [23,25]	Binary classification of ischemia and infection features.	Ischemia Accuracy: 99.65% Infection Accuracy: 84.12%	Deep, multi-layer residual architecture capable of capturing subtle vascular and tissue alterations.	Suboptimal performance in infection isolation from pure RGB data ; absolute lack of explainability mechanisms (black box).
Swin Transformer + EMADN [28]	4-class simultaneous holistic diagnosis (Infection, ischemia, co-existence, normal).	Overall Accuracy: 78.79% F1-score: 80.0%	Shifted-window self-attention allows simultaneous micro- and macro-scale anatomical assessment;	Significantly lower nominal metrics due to multi-class task complexity ; lacks the ability to execute spatial lesion localization.

			native Grad-CAM interpretability.	
XAI-FusionNet [30]	Binary classification (Pathological vs Healthy tissue).	Binary Accuracy: 99.05% F1-score: 99.05%	Exceptional clinical transparency via triple-XAI integration (SHAP, LIME, Grad-CAM) ; hardware-optimized for edge computing.	Limited strictly to primitive binary classification ; cannot physically localize, measure, or qualitatively segment multi-wound beds.
SSODL-DFUDC [31]	Automated, high-throughput binary screening.	Binary Accuracy: 99.29% F1-score: 99.29%	Maximum automated optimization via combined Inception feature extraction and Social Spider Optimization.	Extremely high architectural complexity ; functions entirely as an uninterpretable "black box," reducing clinical trust during edge cases.
EfficientNet-B1 [26,27]	Low-resource mobile and bedside diagnostic classification.	Binary Accuracy: 99.13% F1-score: 99.0%	Multi-dimensional parameter scaling optimizes width, depth, and input resolution with low computational demand.	Lacks native interpretability frameworks ; performance remains highly dependent on intensive pre-processing and data augmentation.

Thermographic imaging and decision fusion systems

A critical consensus across current medical computer vision literature indicates that traditional RGB (Red-Green-Blue) photographic imaging—regardless of network depth—is inherently constrained by superficial surface visual metrics. Consequently, RGB systems routinely fail to isolate subcutaneous physiological anomalies, such as microvascular perfusion deficits or deep-seated inflammatory processes, before they manifest as visible structural ulcers. To resolve this operational blindspot, recent research has pivoted toward infrared thermography paired with machine learning to identify localized skin temperature differentials that serve as early biological markers of diabetic foot syndrome. A novel implementation of this modality combines a decision fusion strategy with lightweight neural network models to process thermal foot profiles. The framework integrates two highly streamlined architectures: MobileNetV2 and ShuffleNet. Selected specifically for their minimal mathematical operational constraints, these networks process independent spatial thermal streams concurrently. The outputs are subsequently fused at the decision-making layer, allowing the joint model to achieve an unblemished 100% classification

accuracy on evaluated test datasets. This absolute accuracy underscores the profound diagnostic advantage of physiological thermal monitoring over pure macroscopic RGB structural analysis (which maxes out at an infection detection threshold of roughly 84–85% using comparable architectures). By converting sub-surface metabolic and inflammatory updates into distinct heat signatures, the MobileNetV2-ShuffleNet ensemble acts as a highly sensitive non-invasive screening tool. Nevertheless, from a clinical translation perspective, thermographic deep learning models face significant implementation bottlenecks. Standardized, high-diversity thermal medical datasets remain profoundly scarce compared to public RGB repositories. Furthermore, current thermographic pipelines lack unified imaging protocols to account for ambient environmental temperatures and lack explainable AI infrastructure, meaning their near-perfect laboratory performance metrics must be validated through rigorous, prospective real-world trials before integration into routine multi-disciplinary care [32,33].

New technologies

Contemporary diagnostics of diabetic foot syndrome (DFU) is no longer based solely on image analysis. Wearable and sensor-based devices are playing an increasingly important role, enabling continuous monitoring of physiological and mechanical parameters. This subsection presents selected examples of the latest technological solutions that may support early DFU detection and help prevent complications.

Smart compression socks with sensors

One of the most innovative preventive solutions in the field of diabetic foot syndrome is smart socks equipped with temperature, pressure, and blood oxygen saturation sensors. The sensors are strategically placed in areas particularly prone to ulcer development, such as the first and fifth metatarsal heads, the hallux, and the heel. Data from the sensors are transmitted automatically every five seconds to a mobile application, which analyzes them in real time and assigns a risk level, ranging from “green,” indicating a stable condition, to “red,” signaling a threat. An integrated SpO_2 sensor additionally enables assessment of tissue perfusion quality. This solution allows early detection of pathological changes without the need for medical visits, and the system automatically generates alerts for both the patient and the medical team [34].

To date, the highest effectiveness in DFU prevention has been demonstrated by socks measuring temperature, as a local increase in temperature often precedes ulcer formation by several days. This enables earlier intervention and may reduce the risk of DFU development by up to 70%. However, these findings must be interpreted with caution. Most existing clinical reports are based on short-term pilot evaluations involving highly homogeneous patient groups. Authors consistently note critical real-world implementation challenges, including the prohibitive cost of

peripheral devices, lower compliance among elderly populations, and a significant lack of large-scale, multi-center randomized controlled trials (RCTs) required to establish long-term clinical efficacy in routine practice [35].

Intelligent pressure-sensing insoles

Solutions such as the innovative insole developed within the "Cyclic Pressure Offloading Insole" project are based on the use of pneumatic chambers that enable cyclic offloading of areas exposed to the highest pressure, primarily in the toes, metatarsal region, and heel. This technology allows dynamic pressure adjustment, including during walking, thereby minimizing peak loads at high-risk sites. The insole can be customized to individual biomechanical characteristics of the patient, such as body weight, gait pattern, or the presence of deformities, which translates into reduced mechanical complications and improved comfort. Nevertheless, the mechanical complexity of pneumatic chamber modulation poses technical limitations regarding durability and potential alteration of overall gait biomechanics, which requires further robust empirical validation [36].

Home monitoring systems – the "Foot Selfie" application

An example of technology that increases patient autonomy in DFU prevention is the "Foot Selfie" system, which enables patients to take photographs of their feet using a dedicated platform and mobile application. The images are automatically transmitted to the medical team, which can assess them remotely. The application reminds users to take regular photographs and allows rapid response if skin changes are detected. Due to its low cost and wide technological availability, this solution has high potential for broad adoption. In studies, 80% of users declared willingness to use the application daily, indicating a high level of acceptance [37].

A similar concept is being developed in an alternative mobile application that also allows patients to take foot photographs using a smartphone. However, unlike Foot Selfie, this solution employs artificial intelligence algorithms for automatic image analysis and preliminary wound classification. Such approaches align with the trend toward increasing patient self-management and enable early detection of changes without the need for an in-person medical visit. Despite high user acceptance, automated image classification via mobile devices in home settings is highly vulnerable to confounding factors such as poor ambient lighting, variable smartphone camera quality, and lack of imaging angle standardization. Furthermore, transmitting sensitive medical imagery over mobile networks introduces rigorous data privacy concerns, cyber-security challenges, and strict regulatory compliance issues (e.g., GDPR) that remain largely unresolved in current clinical frameworks [38].

WoundVue – three-dimensional wound imaging

WoundVue is an advanced system that uses stereophotogrammetry technology to obtain precise three-dimensional measurements of diabetic wounds. It enables contactless measurement of wound area, depth, and volume, making it a safe and non-invasive diagnostic tool. The average measurement error for wound area assessment is less than 3%, ensuring high accuracy even in remote settings. The system can be used within telemedicine frameworks, supporting therapeutic decision-making at a distance without direct patient contact. However, its reliance on specialized hardware primarily limits its widespread application to institutional or advanced clinical environments rather than routine home monitoring [39].

Wearable dressings and PTX sensors

Modern dressings integrated with temperature and pressure sensors, as well as data transmission components such as inductive coils, enable continuous monitoring of physiological parameters without the need for batteries. Owing to high measurement sensitivity and compatibility with mobile devices, these systems provide flexibility and user comfort. A significant advantage is the lack of requirement for precise receiver positioning, which increases convenience in everyday use. This technology enables effective DFU prevention in a manner that is both convenient and non-invasive for the patient. Currently, this technology remains in its early prototype and development phase, completely lacking long-term clinical safety and tissue-compatibility validation [40].

Multimodal systems (e.g. Orpyx®)

Multimodal systems, such as Orpyx®, integrate sensor-equipped insoles, a mobile application, and real-time monitoring of temperature, pressure, and step count. Integration of these data streams enables detection of hazardous loading patterns that may lead to ulcer formation. The system allows automatic adjustment of therapeutic interventions and, through cloud-based data processing, also enables long-term analysis. These solutions support personalized preventive strategies and allow rapid responses to changes in a patient's health status, while simultaneously assisting the physician's decision-making process [41].

Technologies extending beyond traditional measurement of skin parameters are also increasingly being applied. Motion sensors attached to footwear or the lower leg can detect changes in step length, walking speed, or gait stability. Such alterations represent highly valuable early warning signals, as they may indicate an increased risk of ulcer recurrence before any visible changes appear. This broadens clinicians' capabilities by enabling risk assessment at the level of gait biomechanics, rather than being limited to local skin parameters alone [42].

The application of deep learning to the analysis of three-dimensional foot models allows for much more accurate representation of foot morphology and pressure distribution. This may be of key

importance in the design of personalized insoles and protective footwear, which in turn can lead to more effective DFU prevention and a reduced risk of ulcer development. Although this technology is still at an early stage of development, its potential in the context of personalized care appears highly promising (Table IV) [43].

Table IV. Comparative summary of modern technologies in DFU diagnosis and prevention

Technology / Solution	Monitored Parameters	Core Strengths	Clinical Limitations & Challenges	Ref.
Smart Compression Socks	Temperature, pressure, SpO_2	Continuous home monitoring; up to 70% risk reduction in pilot studies.	High device cost; compliance issues; lack of multi-center RCT validation.	[34,35]
Intelligent Offloading Insoles	Dynamic plantar pressure distribution	Active, automated, and personalized pressure unloading during gait.	Mechanical complexity; durability issues; potentially alters gait biomechanics.	[36]
Mobile Applications ("Foot Selfie")	Photographic imaging (RGB) ±AI	Low cost; high patient acceptance (80%); ideal for telemedicine.	Highly sensitive to lighting and image quality; lack of calibration; data privacy (GDPR) risks.	[37,38]
WoundVue System	3D wound geometry & dimensions	Contactless, precise volume and depth mapping (error <3%).	Requires specialized equipment; restricted to institutional or specialized clinical care.	[39]
Battery-free PTX Wearable Dressings	Temperature, localized pressure	Highly flexible; wireless; battery-free; comfortable user experience.	Early experimental stage; complete lack of long-term biological/clinical validation.	[40]
Multimodal Wearable Systems	Pressure, temperature, step metrics	Comprehensive biomechanical data aggregation; cloud-based analytics.	Generates massive data streams (data overload); high commercial barrier.	[41,42]

Discussion

The synthesized literature demonstrates that the most effective approaches for the classification of diabetic foot lesions are the SSODL-DFUDC model, the DFINET-AO architecture combined with PFCNN, and FusionNet. All of these architectures achieve high performance metrics, confirming the dominant role of deep neural networks in image-based diagnostics of the diabetic foot [29,30,31].

To enhance scientific impact and clarify the novel contributions beyond synthesizing recent literature, it is critical to highlight the shifting paradigm in medical image analysis. While foundational architectures (such as ResNet, EfficientNet, and standard Transformer models) are already well-established in general medical imaging, their direct translation to DFU diagnosis

introduces unique constraints [23,25,26,27]. The true innovation within recent high-performance frameworks lies in the strategic combination of semantic lesion segmentation with lightweight backbone models, and the simultaneous integration of explainability layers [26,27,29,30]. For instance, frameworks that couple classification with automated image segmentation offer distinct clinical value by enabling both automated localization of the lesion and qualitative tissue assessment within a single pipeline [29].

Beyond predictive accuracy, the interpretability of model operations represents a core requirement for actual implementation in medical practice. Although certain high-performing black-box models achieve superior accuracy, they do not explicitly explain which image features determined their predictions. In contrast, advanced architectures are increasingly incorporating Explainable AI (XAI) techniques, such as SHAP, LIME, and Grad-CAM, to identify critical regions determining the algorithmic decision. This transparency is crucial for clinical decision-making, converting automated tools from obscure clinical substitutes into reliable interdisciplinary support systems [31]. Thermographic imaging–based methods, such as lightweight networks optimized for mobile environments, further demonstrate a clear potential for rapid, non-invasive detection of sub-clinical pathological changes, although further evaluation is required to confirm their effectiveness across variable real-world hardware configurations [32,33].

However, implementation of deep learning-based systems and wearable devices in clinical practice remains severely constrained by several methodological and structural barriers [4]. While automated models often report lab-based diagnostic sensitivities and accuracies exceeding 99% under laboratory conditions, they are heavily prone to overfitting due to the widespread reliance on small, highly curated, and homogeneous public repositories [4,5,10]. These systems suffer from intense dataset bias, often failing drastically when subjected to external validation across diverse patient populations, variable ambient conditions, or different hardware standards [15].

Furthermore, serious ethical considerations and clinical adoption challenges must be transparently addressed. The legal accountability for diagnostic errors—such as an AI model misclassifying an active infection or ischemic change as healthy—remains entirely on the clinician rather than the software algorithm, fueling professional resistance toward full deployment [44]. Additionally, commercialized frameworks lack clear, standardized Conflict of Interest (COI) disclosures in their published research, raising valid questions regarding potential bias in reporting diagnostic success rates. Lastly, the continuous telemetry required by modern wearable devices generates massive, unstandardized data streams (data overload) that current healthcare IT infrastructures are structurally unequipped to process, manage, or legally secure under international privacy mandates [11,16]. Consequently, even the most high-performance AI architectures or advanced

sensor networks must currently be treated strictly as secondary decision-support mechanisms rather than direct clinical substitutes [5,10,44].

Conclusions

The application of artificial intelligence and emerging technologies in the diagnosis and management of diabetic foot syndrome represents a substantial advancement in contemporary digital medicine. Deep learning models, particularly those integrating lightweight backbone architectures with multi-task semantic segmentation, have demonstrated exceptional diagnostic performance, confirming their potential as reliable clinical decision-support tools. Furthermore, architectures incorporating Explainable AI (XAI) provide an essential layer of transparency necessary for clinician acceptance and safe medical deployment [30]. Beyond image-based diagnostics, wearable and sensor-based technologies facilitate personalized prevention strategies and support remote patient care by enabling continuous monitoring of biomechanical and physiological parameters before clinical manifestations occur [10,15].

Seventy percent potential reductions in ulcer development via remote monitoring are promising [35], but significant challenges must be addressed before widespread translation into routine practice can occur. These include the limited availability of large, diverse datasets, an absence of standardized imaging protocols, and a critical shortage of multi-center, prospective clinical validation [4,5,15]. Practical barriers related to device cost, user compliance, data overload, and data privacy regulations further complicate integration [11,16,44]. Ultimately, artificial intelligence systems cannot replace clinical judgment and must be implemented exclusively as supportive tools within interdisciplinary care models [10]. Future research should focus on large-scale prospective trials, multimodal data integration, and the establishment of robust ethical and legal frameworks for clinical AI deployment [44].

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Ethical considerations

As this study is a literature synthesis and did not involve direct human participants or animals, institutional review board approval was not required. However, the authors emphasize that clinical adoption of the discussed AI technologies must adhere strictly to patient data privacy regulations (e.g., GDPR) and established bioethical standards [44].

Conflict of interest

The authors declare no conflict of interest regarding the publication of this manuscript. None of the commercial systems mentioned have provided financial support, incentives, or funding for this review.

Use of AI tools statement

ChatGPT was used solely for the purpose of integrating and styling the content. The entire research process, including the literature review, analysis of scientific articles, and selection of key information regarding diabetic foot diagnostics, was conducted independently by the authors.

Authors' contribution

Study design – K. Kaleta, J. Adamczyk
Data collection – K. Kaleta, J. Adamczyk, T. Męcik-Kronenberg, M. Kronenberg
Manuscript preparation – K. Kaleta, J. Adamczyk, T. Męcik-Kronenberg, M. Kronenberg
Literature research – K. Kaleta, T. Męcik-Kronenberg, M. Kronenberg
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