AI based Diabetic Foot Ulcer Detection: A Review

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Abstract: Diabetic Foot Ulcer (DFU) is a serious and now commonplace complication for patients with diabetes, and absent timely identification and management, they can lead to infections, hospitalizations, and lower-limb amputations. DFU is a complex combination of peripheral neuropathy, inadequate blood supply, and delayed healing response, making detection and management complicated for all health care systems; urban or rural. AI based detection represents a transformative pathway for diagnosing and managing DFUs early, especially as it relates to patients in low-resource settings. By using computer vision models to analyse wound images, natural language processing (NLP) to interpret clinical notes and patient's symptoms and predictive analytics to stratify risk, AI systems can help healthcare workers better detect DFUs at an earlier stage, with greater accuracy. The systems can assist frontline workers collect structured data, help clinicians assess the ulcer severity based on the usual DFU classifications. Automated detection and classification of DFU using clinical images, structured data, and patient history is feasible through deep learning and machine learning techniques. These methods provide accurate diagnoses, augmented opportunities for early intervention, and support individualization of treatment. This paper presents a comprehensive review of the automatic DFU detection using deep learning and machine learning algorithms.

Keywords: DFU, Deep learning, Machine learning.

I. Introduction

Traditional clinical approaches to DFU detection mainly Manual Assessment, photograph assessment, and thermography find useful diagnostic information through the potential are seen to be subjective, time intensive, and dependant on interpretation. This reveals a clear need for objective and reliable diagnostic alternatives to find solutions to the South African diabetic foot ulcer epidemic. Diabetes mellitus is a chronic metabolic disease that has become a global health challenge. One of the many complications of diabetes mellitus are diabetic foot ulcers (DFUs), which are some of the worst complications of diabetes; involving a large proportion of patients, DFUs result in an increased risk for infection, hospitalization, and lower-limb amputation [1]. The morbidity associated with DFUs impacts in excess of individual patients as it increases morbidity and quality of life and imposes a financial burden on healthcare systems around the world [2]. With the increasing prevalence of diabetes, there are opportunities for new advancements in technology that will help clinicians to detect DFUs more efficiently and accurately. Recent advancements in technology and research create new opportunities for improved diagnostic accuracy and quality of care. Current literature indicates that developing novel, automated approaches to support clinical decision-making and reduce the limits of conventional methods is necessary [3]. In the last few years, artificial intelligence (AI) has judged to be a real opportunity to address these problems. For instance, in the area of medical image analysis, machine learning and deep learning techniques (in particular, convolutional neural networks) have achieved great results. These techniques allow for detection, segmentation, and classification of DFUs with automated performance that is often superior to traditional methods. Hybrid models that combine handcrafted features with deep learning representations have even greater potential. Additionally, new frameworks that focus on explainability in AI systems may help to address the "black-box" problem of deep learning models, providing clinicians with clear and interpretable results in their practice and therefore allowing for more trust in an AI-assisted diagnosis. DFUs have a multifactorial pathogenesis that includes neuropathy, ischemia, impaired healing and/or structural deformities, and in particular, deformities are important because they influence the plantar pressure distribution and, in turn, skin breakdown and ulceration [4]. Once they occur, DFUs are very difficult to treat because sealing is complicated by poor blood supply and recurrent infections. Current standardized approaches to DFU detection and risk assessment, including visual inspection and measurement of plantar pressures, are all limited to a large extent by errors, and ingrained bias and dependence on the clinician’s skill set. Even with promising strides forward there are still barriers for the routine introduction of AI-based systems into clinical practice. It is worth sufficiently acknowledging the issue of datasets, discrepancies with DFU classification and the inability to generalise a model across different populations of individuals and imaging conditions. Although, it certainly requires advanced and ethical AI systems that are trustworthy and robust, for society to be completely accepting of these implementations into clinical practice. Future research to make progress in these areas would surround improvements in interpretability, generating synthetic datasets for model training, and developing light weight and real-time frameworks that can be seamlessly introduced into clinical workflows. Convolutional Neural Networks (CNNs) have proven to be extremely effective, outperforming traditional machine learning (ML) approaches in image-based recognition tasks in accuracy and robustness [5]. Utilizing hybrid methods that incorporate handcrafted features and CNN-based deep features, the detection accuracy and precision of classifying infection and ischemia has improved markedly [6]. Interpretable AI models that offer explanation features like SHAP, LIME, and Grad-CAM in addition to their AI capabilities are currently available, offering clinicians invaluable transparency by localizing the ulcer with visual heatmaps. This paper is organized as follows: section II provides literature review, research challenges are provided in Section III and Section IV concludes the article.

II. Related work

The author identified deepness of a wound, infection and ischemia as an amputation risk [1]. The usage of photographic imaging and infrared thermography has been considered to determine foot infection in diabetic patients. The purpose of using photographic imaging and infrared thermography was to facilitate the early detection of foot infections, for high-risk diabetic patients who are monitored at home [1]. Fully Convolutional Networks (FCN) have been developed to segment diabetic foot ulcers [2]. The implementation of deep neural networks in health care has been studied extensively, and many journals in the scientific literature have examined the possibilities in acquire depth and breath. The author also indicated to the introduction of a CNN for the classification of diabetic foot ulcers. Also, a staged assessment of symptoms of foot infection in diabetic patients has been developed with photographic imaging and infrared thermography. The author highlighted the opportunity and the potential use of deep learning methods for training FCNs that automatically recognize and segment the DFU and the surrounding skin region with a relatively high level of accuracy [3]. Mehnoor Ahsan et al. [4] have proposed a variety of end to end CNNs architectures for diabetic foot ulcer detection.

Using CNN models, the authors have studied visual features for infection and ischemia classification with the DFU2020 dataset. The proposed methods for DFU classification and recognition are transfer learning methods with fine-tuned weights from source and target domains. The results show that for ischemia and infection, ResNet50 has the highest accuracies of 99.49% (infection) and 84.76% (ischemia). In the paper [5], a CNN architecture was proposed based on residual blocks for identifying high-level features. Combining features with different machine learning methods gives higher accuracy for DFU recognition, than if using individual features.

The proposed methodology thus enhanced autonomous diagnosis of diabetic foot ulcer (DFU) images by fusion of low-level features from machine learning classifier and high-level features from CNN. A diabetic foot-infection network has been proposed for detecting infected and non-infected foot using DFU images [6]. The proposed CNN model integrates parallel convolution layer features for compact representation with some specific and important features representing the foot infection. To make it possible to understand the infection because when it is looked at, it is more profitable to treat problematic conditions that appear not to be infected skin. In the study [7] the authors proposed four hybrid CNN architectures for DFU identification. The recommended model incorporates traditional convolutional layers and an average pooling layer along with six blocks of parallel convolutional layers. The model developed with four parallel convolution layers outperformed that with five, three or two parallel convolutions. The dataset

has been collected from Nasiriyah Hospital in Iraq, and all pertinent parties, including patients provided ethical approval and signed consent.
The objective of this study [8] was to develop a valid pedographic classification system to classify diabetic patients according to their risk for foot ulceration, accounting for the limitations in previous methodology where no pressure threshold had been established. Overall, 210 patients (120 diabetics, 90 non-diabetics) were categorized into four subgroups reflecting specific foot deformity, with measurements taken for plantar pressure between the eleven regions of the foot using a percentage mask and an anatomical mask. The key pedographic variables peak pressure, force and their time integrals were analyzed using multivariate logistic regression. It was found that for the percentage mask, four variables (pressure time integral of forefoot, peak pressure at midfoot, pressure time integral of heel, peak pressure at heel) were able to identify patients with ulcers with 73% sensitivity and 87% specificity. The anatomical mask approach had eight contributing regions (metatarsal heads, great toe, etc.) that offered greater precision with 95% sensitivity and 90% specificity.
Van Netten et al. (2013) [9] investigated the feasibility of using high-resolution infrared thermal imaging, with the aim for automated detection of diabetic foot complications as noninvasive approach, the main challenge which is early identification of diabetes foot complications in high risk individuals. Note that an increased plantar foot temperature would be an early sign of inflammatory processes and potentially ulceration, the authors developed further from previous studies which established temperature differences across contralateral foot regions were an early indicator of ulcer development. Previous clinical studies using hand-held thermometers demonstrated that a temperature difference of greater than 2.2° C could be a useful clinical threshold for intervention, but previous studies were limited despite the utility of obtaining thermometric data because of low resolution, manual operation and therefore lack of automation. Researchers can mitigate this in infrared imaging, as they could include a fully automated analysis with generally high spatial resolution and would not limit telemedicine applications. In order to validate their approach, authors applied their methodology to diabetic patients, recruitment and screening of levels of diabetic foot complications (none, local, and diffuse). Researchers determined that temperature differences > 2 ° C indicated local complications such as callus or ulcers, while differences > 3 ° C indicated diffuse complications such as Charcot foot or osteomyelitis.
Diabetic foot ulcers (DFUs) are a common and serious complication of diabetes, resulting in increased morbidity to patients and strain on the healthcare system. This [10] systematic review reported the current applications and accuracy of ML in any aspect DFU care and management. The included studies applied different types of algorithms to a variety of tasks including image segmentation and classification, raw data analysis, and risk assessments. The authors reported that included studies reported at least one appropriate algorithm with at least 90% accuracy compared with a gold-standard method. Although overall findings suggest that ML offers

potential advantages to DFU data analysis and outcomes, the studies considered were limited in public health significance due to the small sample size or study-specific study design.

This study [11] has assessed the implementation of deep learning techniques, specifically CNNs for the automatic detection and classification of diabetic foot ulcers (DFUs) in clinical images. The authors has created an entire framework that pre-processed the wound images to normalize for lighting, remove background, and segment the ulcer area prior to classification into severity classification. The model exhibited high accuracy, sensitivity, and specificity from adult labelled DFU images, indicating its potential for clinicians to facilitate early diagnosis and monitoring of DFUs. The findings suggest that deep learning can help TA efficiency and objectivity in DFU evaluation; however, further validation with large suitably diverse datasets should be conducted before clinical application.

Traditional DFU clinical examinations and care require a great deal of vigilance from both the patient and clinician which is often prohibitively costly and time consuming, among other challenges and barriers. The authors have managed to collect a substantial dataset of foot images from various patients, framed a binary classification task to distinguish healthy skin from DFU affected skin, and also proposed a highly novel convolution neural network architecture, DFUNet, which allows for better feature extraction for DFU characterization while simultaneously producing predictions with high accuracy [12]. Using 10-fold cross-validation DFUNet yielded a 0.961 AUC with regard to accuracy and performance; outperforming both traditional machine learning and existing deep learning classifiers tested. This study serves an evidence-based example demonstrating the future potential of DFUNet being a platform for low-cost, remote, cost-efficient and objective DFU detection, representing the latest advance in diabetic foot care. The study outlined several obstacles to the clinical uptake of AI for DFU that need to be addressed—improving model interpretability, broadening diverse dataset access, and alleviating the process of acquiring and annotating DFU images for model developers [13]. AI has a strong potential to improve DFU management, but several practical barriers will hinder the uptake of this technology in clinical practice. Data collection and labelling takes significant time and resources, while imperfect and inconsistent DFU classification and lack of standardised datasets from zrosted image acquisition conditions and population variability remained barriers for model reliability. Smartphone applications proposing AI-based innovations have their own barriers are limited interpretability, poor generalisability across different patient populations, and ethical concerns within predictive modelling, such as bias. It is important to address these issues with transparent, inclusive, and ethically governed AI-based applications, so that trust in this technology can be augmented, and clinical uptake of this technology can be facilitated.

Recent progress in deep learning, particular convolutional neural networks (CNNs), have exhibited considerable promise in DFU classification, detection, and segmentation. The performance characteristics of these models are contingent on the availability and quality of the training datasets, however, publicly available datasets will allow for data augmentation, unbiased

benchmarking, and testing of preprocessing techniques (i.e., contrast enhancement, noise filtration, color normalization) [14].
DFUs are a serious health threat that can lead to amputations if not detected early. Although imaging-based technologies are currently used to detect DFUs, they are limited in the amount of information they present, are computationally intensive, and the results lack generalizability. To overcome the limitations of imaging analysis, this paper proposed a novel hybrid diagnostic framework that allows for hand-crafted and deep learning (DL) features for the early, real-time computer-assisted detection of DFUs, based on plantar thermograms [15]. In this proposed model, the authors used ORB-based hand-crafted features fused with deep CNN features from pre-trained CNN methods (e.g. ResNet50, AlexNet, EfficientNet). The ORB and CNN feature fusion is classified with a small deep neural network. Experimental studies on a plantar thermograms dataset (n = 1670) revealed a state-of-the-art performance, identified by measures of 98.51% accuracy, 100% precision, and AUC of 1.00. These results exceeded existing DFU detection models (e.g. DFU_VIRNet and DFU_QUTNet), while also demonstrating our ability to achieve real-time capabilities.
To support interpretable detection of DFUs, the authors developed the DFU_XAI framework, which incorporates advanced deep learning techniques with lightweight architectures, such as Xception, DenseNet121, ResNet50, InceptionV3, MobileNetV2, and Siamese Neural Networks (SNN), combined with explainable methods, such as SHAP, LIME, and Grad-CAM [16]. The SNN demonstrated the best performance with a 98.76% accuracy, as well as high precision, recall, and AUC. We also used Grad-CAM for an additional layer of explainability, which allowed for visual localization of the ulcers for the clinician team. Even though there are still some challenges with the overall transparency and trust of the AI systems, the DFU_XAI framework incorporates new possibilities of AI into diabetic foot care by addressing the limitations of DFU delivery models that are typically reliant on labour intensive methods, while also providing a reliable method that has clinical relevance.
Automated identification and classification of DFUs remains a difficulty, and it is especially challenging to visually distinguish ischemic diabetic foot ulcers from infectious ones. This paper explored transfer learning and evaluated seven pretrained deep convolutional neural network (DCNN) models: EfficientNetB0, DenseNet121, ResNet101, VGG16, MobileNetV2, InceptionV3, and InceptionResNetV2 for the detection of diabetic foot ulcers [17]. A new model E-DFu-Net was proposed to accurately classify DFUs and mitigate over-fitting and improve accuracy by combining key features of existing architectures. The experiment was able to provide data indicating that E-DFu-Net achieved 97% accuracies classifying ischemia and 92% accuracies classifying infections while outperforming conventional models. This research demonstrates that transfer learning and custom hybrid architectures are promising methods for improving reliable and accurate diabetic foot ulcer diagnoses and for informing future clinical decision-making and protocols.

The DFU_XAI framework was created to increase transparency in deep learning (DL)-based DFU detection by utilizing explainable AI techniques in clinical decision-making. In this paper [18] the DFU_XAI framework examined the performance of five pretrained DL models (Xception, DenseNet121, ResNet50, InceptionV3, and MobileNetV2) through the lens of explainability with the interpretability methods such as SHAP, LIME, and Grad-CAM. The ResNet50 model had the best performance when using DFU segmentation with an accuracy of 98.75%, precision of 99.2%, and an AUC of 98.5%, and the Grad-CAM heat maps accurately outlined areas indicating a DFU. In sum, the framework showed promising evidence of being able to successfully differentiate between DFUs and healthy feet, and closely localise the ulcer site, increasing both the accuracy of the diagnosis and interpretability of the model.

Table 1. Comparative analysis of literature review

Author	Method	Dataset	Key Results	Strengths	Limitations
Armstrong et al., 1998	Clinical wound classification (depth, infection, ischemia)	Clinical patient data	Validated DFU risk classification	Identify risk factors	Manual, subjective
Goyal et al., 2017	Fully Convolutional Networks (FCN)	DFU images	High accuracy in segmentation	Automated segmentation	Requires large datasets
Hazenberg et al., 2019	Photographic imaging & infrared thermography	Foot images	Early detection of infection	Non-invasive, home monitoring	Limited precision, lighting issues
Ahsan et al., 2023	End-to-end CNN architectures	DFU2020 dataset	ResNet50: 99.49% (infection), 84.76% (ischemia)	High performance classification	Ischemia detection still lower
Das et al., 2021	Fusion of handcrafted + CNN features	DFU images	Improved accuracy vs. individual models	Combines ML & DL	Computationally heavy
Yogapriya et al., 2022	CNN model for infection detection	DFU dataset	High accuracy in infection classification	Specific to infection	May not generalize
Alzubaidi et	Hybrid CNN	DFU images	Parallel	Robust feature	Dataset-specific

Author	Method	Dataset	Key Results	Strengths	Limitations
al., 2021	architectures	(Iraq hospital)	convolution layers improved performance	extraction	
Waldecker, 2012	Pedographic classification (plantar pressure)	210 patients	Sensitivity 95%, Specificity 90%	Clinical risk stratification	No image analysis
Van Netten et al., 2013	Infrared thermal imaging	Diabetic patients	ΔT > 2°C = local complications	Early detection	Manual limitations
Tulloch et al., 2020	Systematic review of ML in DFU	Multiple datasets	ML ≥90% accuracy in many tasks	Summarizes field progress	Small, limited studies
Goyal et al., 2020	DFUNet (CNN architecture)	DFU dataset	AUC 0.961	Outperforms ML & DL baselines	Dataset dependency
Alkhalefah et al., 2025	AI & Generative AI for DFU	Clinical + synthetic data	Improved classification & segmentation	Synthetic data augmentation	Early-stage adoption
Selavaraju et al., 2025	DL with preprocessing (contrast, noise reduction)	Public DFU datasets	Better accuracy with ResNet, DenseNet, U-Net	Strong preprocessing pipeline	Requires high-quality data
Eldin et al., 2025	Lightweight DNN with thermograms	1670 plantar thermograms	Accuracy 98.51%, AUC 1.0	Real-time, robust	Limited to thermal images
Rathore et al., 2025	Explainable DL (SHAP, LIME, Grad-CAM)	DFU images	High accuracy + visual explanations	Increases interpretability	Still evolving
Almufadi et al., 2025	E-DFu-Net (hybrid CNN)	DFU datasets	97% (ischemia), 92% (infection)	Reduces overfitting	New, needs validation
Biswas et al., 2024	DFU_XAI (Explainable AI framework)	DFU datasets	SNN: 98.76% accuracy	Strong explainability	Needs clinical integration

III. Research Challenges in AI-based DFU Detection:

i. Classification Inconsistencies

Varying inconsistencies in DFU classification methods across studies impede effective model training and benchmarking, further complicating reproducibility and comparability.

ii. Interpretability of AI Models

Most deep learning models are viewed as "black boxes," which will inherently limit the clinical trust that can be placed in these technologies. Explainable AI methods such as SHAP, LIME, or Grad-CAM still need to be developed sufficiently for clinical use.

iii. Generalization and Bias

Models can often perform very poorly on new populations or datasets not representative of the training domain. This means we need to be aware of ethical concerns (potential bias) around prediction.

iv. Clinical Integration Challenges

To be practically deployable in clinical practice, models must be lightweight, real time, and integrate into existing workflows, even when performing highly in a research context.

IV. **Conclusions**

DFUs are an important complication of diabetes associated with amputation, costing patients and healthcare systems significant technical and functional impairment. This review has illustrated that AI, especially machine learning and deep learning, provides a feasible method of automated detection, classification, and management of DFUs. Machine learning and deep learning have changed the landscape for early recognition, classification, and decisions regarding the management of DFUs through image-based analysis and decision support. Convolutional neural networks, as well as hybrid models utilizing hand-crafted features along with deep representations, have reached levels of accuracy never seen before; and explainable AI strategies such as SHAP, LIME, and Grad-CAM are providing clinicians with a new level of observability and trust, which is important when building clinical trust. Still, machine learning and deep learning methods will be limited unless datasets and protocols exist that allow sufficient generalization when utilizing machine learning and deep learning across populations, along with inherent challenges such as varied degrees of DFU classifications and variants of management techniques associated with DFUs, as well as the inherent black-box nature of deep learning. In order to gain clinical acceptance, machine learning and deep learning approaches must become interoperable with real-life workflows, be interpretable, ethically sound, and computationally efficient. If adequately resolved, there is a possibility that all the approaches could reduce the technical, opportunity and financial burden of DFUs by streamlining patient access to timely, cost-effective and accurate interventions and care that can improve outcomes and decrease the impact of diabetic foot complications globally.

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