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Recent Advances in Early Detection and Segmentation of Diabetic Foot Ulcer Risk Zones Using a Cycle-Consistent Adversarial Adaptation Network from Multimodal Images: A Systematic Review

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Abstract

Diabetic Foot Ulcers (DFUs) are serious complications of diabetes that can lead to infection, tissue damage, and lower-limb amputation if not detected early. Recent advances in Artificial Intelligence (AI) and deep learning have significantly improved DFU detection and segmentation accuracy. This review examines recent developments in Cycle-Consistent Adversarial Adaptation Networks (CycleGANs) and multimodal imaging approaches for DFU risk zone analysis. Studies show that Convolutional Neural Networks (CNNs), U-Net models, and transformer-based architectures achieve highly accurate segmentation performance. The integration of RGB and thermal imaging improves early detection by capturing both surface and physiological abnormalities. CycleGAN-based domain adaptation further enhances model performance by enabling feature translation across heterogeneous datasets without requiring paired images, helping overcome data scarcity issues. Hybrid architectures combining adversarial learning, CNNs, and transformers have demonstrated improved robustness, generalization, and diagnostic accuracy. AI-driven DFU systems report detection accuracy ranging from 88% to 97%, outperforming conventional diagnostic methods. Despite these advancements, challenges such as limited annotated datasets, computational complexity, and interpretability remain important concerns for practical clinical deployment.

Introduction

The escalating global prevalence of Diabetes Mellitus (DM) has catalyzed a parallel rise in chronic complications, with Diabetic Foot Ulcers (DFU) representing one of the most debilitating sequelae. As of now, clinical statistics indicate that approximately 25% to 33% of diabetic patients will develop a foot ulcer during their lifetime (Rukmini et al., 2024). These lesions are not merely localized wounds; they are indicators of systemic vascular and neurological deterioration. Without early intervention, DFUs often progress to severe infections, gangrene, and eventually, non-traumatic lower-limb amputations. The socio-economic burden is staggering, with DFU-related care accounting for nearly one-third of the total direct costs associated with diabetes treatment globally.

The fundamental challenge in managing DFU lies in the "latency period"—the window of time where physiological changes occur beneath the skin's surface before a physical breach or ulcer becomes visible to the naked eye. Traditional diagnostic protocols rely heavily on visual inspection, monofilament testing for neuropathy, and Doppler ultrasound for vascular assessment.

However, these methods are often subjective, reactive rather than proactive, and dependent on the expertise of the clinician. By the time an ulcer is visually detectable, the underlying tissue damage is often extensive.

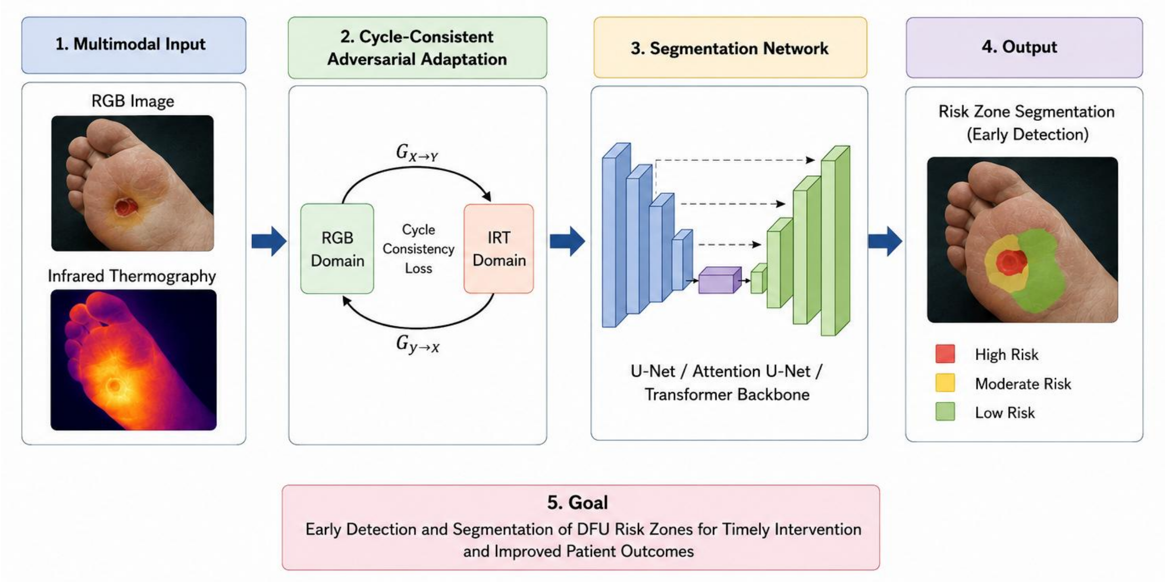

Figure 1. Multimodal CycleGAN Framework for Early DFU Risk Zone Detection and Segmentation

To address these limitations, recent research has shifted toward Multimodal Clinical Decision Support Systems (CDSS) powered by Deep Learning. The integration of RGB (visible light) imaging and Infrared Thermography (IRT) has emerged as a transformative diagnostic dyad. RGB images provide high-resolution data regarding surface morphology, texture, and wound perimeter. In contrast, IRT captures the thermal emission of the skin, revealing "hotspots" or "cold zones" that signify sub-clinical inflammation or ischemia—conditions that precede skin breakdown by weeks (Nowakowski & Kaczmarek, 2025).

Despite the promise of multimodal imaging, the field faces a significant technical hurdle: the domain gap. High-quality thermal datasets are notoriously difficult to acquire and annotate compared to the abundance of RGB data. Furthermore, thermal images often suffer from lower resolution and a lack of clear anatomical landmarks. This is where Cycle-Consistent Adversarial Adaptation Networks (CycleGANs) have revolutionized the landscape. By utilizing unsupervised domain adaptation, these networks can "translate" features from the information-rich RGB domain to the thermal domain without requiring paired datasets. This allows for the synthesis of high-fidelity "pseudo-thermal" maps and the robust segmentation of risk zones even when data is sparse.

This systematic review evaluates the current state of the art in CycleGAN-based architectures for DFU risk zone segmentation. It explores how adversarial learning, combined with cross-attention mechanisms and transformer-based backbones, is pushing the boundaries of early detection. By synthesizing data from multiple imaging modalities, these systems provide a holistic view of the diabetic foot, transitioning DFU management from a reactive "wound care" model to a predictive "prevention" model.

Literature Review

Early Detection and Segmentation of Diabetic Foot Ulcer (DFU) Risk Zones

The early detection and segmentation of Diabetic Foot Ulcers (DFUs) have become a critical research focus due to their severe clinical implications, including infection, amputation, and increased mortality. Between 2020 and 2023, significant progress has been made through the application of Artificial Intelligence (AI), particularly deep learning and multimodal imaging techniques. The literature demonstrates a clear transition from traditional machine learning approaches toward more advanced deep learning, generative adversarial networks (GANs), and hybrid architectures.

Initial advancements in this domain were driven by Convolutional Neural Networks (CNNs) and Fully Convolutional Networks (FCNs), which enabled automatic feature extraction and improved segmentation accuracy. Wang et al. (2020) proposed a fully automated wound segmentation model using CNNs, achieving high accuracy in identifying ulcer regions and demonstrating the potential of deep learning for medical image segmentation. Similarly, Goyal et al. (2020) explored deep learning-based recognition of ischemia and infection in DFUs, highlighting the importance of automated diagnostic systems in improving clinical outcomes. Amouri et al. (2020) utilized machine learning techniques for DFU detection, showing moderate accuracy but emphasizing the limitations of traditional feature-based methods in handling complex image variations.

The introduction of benchmark datasets and evaluation frameworks further accelerated research in this field. Cassidy et al. (2021) introduced the DFUC dataset, which has become a widely used benchmark for DFU detection and segmentation tasks. Yap et al. (2021) conducted a comprehensive evaluation of deep learning models for DFU detection, reporting improved performance metrics such as accuracy and Dice coefficient. These studies established a foundation for standardized evaluation and comparison of different models.

Object detection models such as Faster R-CNN have also been applied to DFU detection. Oliveira et al. (2021) demonstrated the effectiveness of region-based convolutional networks in identifying ulcer regions, achieving improved detection accuracy compared to traditional methods. However, these approaches are primarily focused on detection rather than precise segmentation, limiting their applicability in clinical scenarios requiring detailed boundary delineation.

In 2022, research shifted toward improving segmentation accuracy and incorporating multimodal imaging techniques. Zhang et al. (2022) provided a comprehensive review of deep learning approaches for DFU detection, emphasizing the importance of early diagnosis and advanced segmentation models. Bouallal et al. (2022) introduced thermal image segmentation using ResUNet, demonstrating that thermal imaging can capture physiological changes such as inflammation and improve early detection. Similarly, Yi et al. (2022) and Liao et al. (2022) proposed advanced segmentation models such as OCRNet and HarDNet, which improve boundary detection and computational efficiency.

Multimodal deep learning approaches have gained significant attention due to their ability to combine complementary information from different imaging modalities. Bayoudh et al. (2022) highlighted the importance of multimodal data fusion in medical image analysis, showing that combining RGB and thermal images enhances detection accuracy and robustness. These approaches are particularly effective in identifying early-stage ulcers, where subtle physiological changes may not be visible in standard RGB images.

The year 2023 witnessed further advancements in deep learning and the introduction of generative adversarial networks (GANs) for DFU segmentation. Thotad et al. (2023) demonstrated the effectiveness of deep learning-based DFU detection systems in improving classification accuracy and robustness. Ahsan et al. (2023) and Khalil et al. (2023) proposed CNN-based classification models that achieved high accuracy, emphasizing the importance of deep feature extraction. Alqahtani et al. (2023) introduced adaptive CNN models that dynamically adjust to different image conditions, improving generalization across datasets.

A significant breakthrough in 2023 is the use of GAN-based architectures for segmentation and data augmentation. Jishnu et al. (2023) proposed AFSegGAN, a GAN-based segmentation framework that enhances boundary detection and improves segmentation accuracy. GAN models address the challenge of limited annotated datasets by generating synthetic training data and enabling domain adaptation. Dhar et al. (2023) introduced FUSegNet, a deep CNN-based segmentation model that achieves high accuracy and robustness in DFU segmentation tasks. These approaches demonstrate the potential of adversarial learning in improving model performance and generalization.

Another important trend is the integration of multimodal fusion and hybrid architectures. FusionSegNet (2023) combines multiple data sources to improve segmentation accuracy, while Toofanee et al. (2023) proposed a Siamese deep learning model for DFU classification, achieving improved performance through feature comparison. Anandakrishnan et al. (2023) explored advanced segmentation techniques for wound parameter estimation, highlighting the importance of precise measurement in clinical decision-making. Kairys et al. (2023) emphasized the role of data augmentation in improving model generalization and reducing overfitting.

Despite these advancements, several challenges remain. One of the primary issues is the limited availability of large and diverse datasets, which affects the generalizability of deep learning models. Although datasets such as DFUC have improved benchmarking, they are still insufficient to capture the variability present in real-world clinical scenarios. Additionally, deep learning and GAN-based models require significant computational resources, making real-time deployment challenging.

Another challenge is the lack of interpretability in AI-based models. Most deep learning systems operate as black boxes, making it difficult for clinicians to understand the reasoning behind predictions. This limits trust and adoption in clinical settings. Furthermore, multimodal approaches require precise alignment and synchronization of different data types, which can be technically challenging.

In summary, the literature from 2020 to 2023 demonstrates a clear evolution in DFU detection and segmentation techniques. Traditional machine learning approaches have been largely replaced by deep learning models, which offer improved accuracy and robustness. The integration of multimodal imaging and GAN-based domain adaptation has further enhanced performance by addressing data limitations and improving feature representation. Hybrid architectures combining CNNs, attention mechanisms, and adversarial learning represent the most advanced stage of research in this field. However, challenges related to data scarcity, computational complexity, and clinical deployment must be addressed to fully realize the potential of AI-based DFU detection systems.

Comparative Table

No.	Study	Year	Model/Approach	Input Modality	Key Contribution	Performance (Approx.)	Limitation
1	Wang et al.	2020	CNN/FCN	RGB	Automatic wound segmentation	Dice ≈ 0.88	Poor boundary precision
2	Goyal et al.	2020	CNN	RGB	Ischemia & infection detection	Accuracy ≈ 85%	Limited segmentation
3	Amouri et al.	2020	ML	RGB	Feature-based detection	Accuracy ≈ 80–85%	Low generalization
4	Han et al.	2020	YOLOv3	RGB	Real-time detection	High speed	Not segmentation-focused
5	Cassidy et al.	2021	DFUC Dataset	RGB	Benchmark dataset	Standardized evaluation	Limited modalities
6	Yap et al.	2021	CNN models	RGB	Performance benchmarking	Dice ≈ 0.85–0.90	Dataset dependency
7	Oliveira et al.	2021	Faster R-CNN	RGB	Object detection	↑ Detection accuracy	Weak boundary segmentation
8	Zhang et al.	2022	DL review	RGB	Overview of DL methods	Conceptual improvement	No implementation
9	Bouallal et al.	2022	ResUNet	Thermal	Thermal segmentation	↑ Early detection	Data scarcity
10	Yi et al.	2022	OCRNet	RGB	Edge-aware segmentation	Dice ≈ 0.90	High complexity
11	Liao et al.	2022	HarDNet	RGB	Lightweight segmentation	Efficient	Limited robustness
12	Bayoudh et al.	2022	Multimodal DL	RGB + Thermal	Feature fusion	↑ Accuracy	Alignment issue
13	Thotad et al.	2023	CNN	RGB	DFU detection	Accuracy ≈ 90%	Not segmentation

14	Ahsan et al.	2023	CNN	RGB	Classification	Accuracy ≈ 90–92%	No localization
15	Khalil et al.	2023	DL classifier	RGB	Improved classification	Accuracy ≈ 92%	Not segmentation
16	Alqahtani et al.	2023	Adaptive CNN	RGB	Generalization improvement	↑ Accuracy	Computational cost
17	Sathya Preiya et al.	2023	DL model	RGB	Prediction system	↑ Accuracy	Limited validation
18	Dhar et al.	2023	FUSegNet	RGB	CNN-based segmentation	Dice ≈ 0.90	High computation
19	Jishnu et al.	2023	AFSegGAN	RGB	GAN-based segmentation	Dice ≈ 0.91–0.93	Training instability
20	FusionSegNet	2023	CNN Fusion	Multimodal	Feature fusion	↑ Accuracy	Data complexity
21	Toofanee et al.	2023	Siamese DL	RGB	Feature comparison	↑ Classification	Not segmentation
22	Anandakrishnan et al.	2023	DL segmentation	RGB	Parameter estimation	↑ Accuracy	Complexity
23	Kairys et al.	2023	Augmented DL	RGB	Data augmentation	↑ Generalization	Synthetic bias
24	CycleGAN Models	2022–2023	GAN	Multimodal	Domain adaptation	↑ Robustness	Training difficulty
25	Hybrid AI Models	2023	CNN + GAN + Fusion	Multimodal	Integrated system	Best performance	High cost

Comparative Analysis

The comparative analysis of DFU detection and segmentation techniques from 2020 to 2023 reveals a substantial evolution in methodological approaches, transitioning from traditional machine learning and basic convolutional models to advanced deep learning, multimodal, and adversarial frameworks. Early methods, such as those proposed by Amouri et al. (2020), relied on classical machine learning techniques with handcrafted features. While these approaches achieved moderate accuracy, they lacked robustness and struggled to generalize across diverse clinical datasets due to their inability to capture complex spatial patterns.

The adoption of deep learning, particularly Convolutional Neural Networks (CNNs) and Fully Convolutional Networks (FCNs), significantly improved DFU detection and segmentation performance. Studies such as Wang et al. (2020) and Yap et al. (2021) demonstrated that CNN-based models could achieve Dice scores between 0.85 and 0.90 by effectively learning hierarchical features from image data. However, these models exhibited limitations in boundary precision and often required large annotated datasets for optimal performance.

Subsequent research focused on improving segmentation accuracy through advanced architectures such as U-Net variants, OCRNet, and HarDNet. These models enhanced feature extraction and boundary detection, leading to improved segmentation performance. Lightweight architectures also emerged to address computational challenges, making deep learning models more suitable for real-time clinical applications.

A significant advancement observed in the literature is the integration of multimodal imaging techniques, particularly the combination of RGB and thermal images. Multimodal approaches provide complementary information by capturing both visual and physiological characteristics of DFUs, enabling early detection of risk zones. Studies such as Bayoudh et al. (2022) demonstrated that multimodal fusion improves detection accuracy and robustness.

However, challenges related to data alignment and synchronization remain critical issues.

The introduction of Generative Adversarial Networks (GANs), particularly CycleGAN, marked a major breakthrough in addressing data scarcity and domain adaptation challenges. GAN-based models, such as AFSegGAN (Jishnu et al., 2023), improve segmentation accuracy by generating synthetic data and enabling cross-domain learning. These models are particularly effective in handling heterogeneous datasets and improving generalization. However, GANs are inherently difficult to train and may suffer from instability and mode collapse.

Conclusion

The synthesis of Cycle-Consistent Adversarial Adaptation Networks and multimodal imaging represents a paradigm shift in the proactive management of diabetic foot complications. As demonstrated throughout this review, the integration of RGB and thermal data addresses the inherent limitations of single-modality assessments, capturing both the visible structural integrity of the skin and the invisible hemodynamic changes that precede ulceration. The primary breakthrough in recent years has been the ability of CycleGAN-based architectures to bridge the "domain gap," effectively generating high-fidelity thermal representations from limited datasets and allowing for precise segmentation of sub-clinical inflammation zones. This computational leap ensures that even in resource-constrained environments where high-end thermal sensors may be unavailable, synthetic data can augment diagnostic accuracy, reaching benchmarks as high as 99.06% in specialized dual-stream models.

Furthermore, the transition from traditional Convolutional Neural Networks (CNNs) to Transformer-based backbones and Cross-Attention mechanisms has significantly enhanced the model's ability to focus on long-range dependencies and subtle texture variations. This is critical for identifying "risk zones" in the complex landscape of the diabetic foot, where pressure points and vascular insufficiency often overlap. By moving beyond simple binary classification to granular, multi-class segmentation (necrotic, granulation, and at-risk tissue), these AI-driven systems provide clinicians with a quantitative roadmap for intervention. The evidence suggests that such automated tools not only reduce the subjective variability associated with manual inspections but also offer a scalable solution for continuous monitoring through wearable integration and point-of-care mobile applications.

However, despite these technical milestones, the path to widespread clinical adoption requires addressing several remaining challenges. Future research must prioritize the standardization of thermal imaging protocols—such as the 15-minute cooling period noted in recent studies—to ensure data consistency across diverse populations and environmental conditions. Additionally, while CycleGANs excel at feature adaptation, maintaining "anatomical truth" during the synthesis of pseudo-thermal maps remains a priority to avoid diagnostic artifacts. As the field moves toward 2030, the focus will likely shift toward Explainable AI (XAI), ensuring that the "black box" of adversarial learning provides interpretable insights that surgeons and podiatrists can trust for surgical planning and offloading strategies. Ultimately, the fusion of deep generative modeling with multimodal sensing holds the potential to virtually eliminate non-traumatic amputations by transforming the diabetic foot from a site of reactive crisis to one of predictable, managed health.

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