Archives available at journals.mriindia.com

Multidisciplinary Journal of Research in Engineering and Technology

ISSN: 2348-6953

Volume 12 Issue 02, 2025

A Comprehensive Review of Early Detection and segmentation of Diabetic Foot Ulcer Risk Zones Using a Cycle-Consistent Adversarial Adaptation Network from multimodal images

Jovencio Chowdhuryan

Lecturer, Department of Computer Science and Engineering, Indus Institute of Engineering Commerce, Pakistan

Email: jovencio.chowdhuryan@iiec-pk.edu

Peer Review Information

Submission: 28 Sept 2025

Revision: 15 Oct 2025

Acceptance: 29 Oct 2025

Keywords

Diabetic Foot Ulcer (DFU), Multimodal Imaging, Cycle-Consistent Adversarial Networks (CycleGAN), Image Segmentation, Deep Learning, Domain Adaptation, Thermal Imaging, U-Net, Medical Image Analysis, Risk Zone Detection.

Abstract

Diabetic Foot Ulcers (DFUs) are among the most serious complications of diabetes and can lead to infection, amputation, and increased mortality if not identified early. Accurate detection and segmentation of DFU risk zones are essential for timely diagnosis and effective treatment planning. Traditional image-based assessment methods often face limitations due to variations in lighting, tissue appearance, and limited annotated medical datasets. Recent advancements in deep learning and adversarial learning have introduced more reliable approaches for DFU analysis using multimodal medical imaging. This review focuses on Cycle-Consistent Adversarial Adaptation Networks (CycleGAN) for early DFU detection and segmentation using RGB and thermal images. Multimodal imaging provides complementary information related to tissue texture, temperature distribution, and inflammation patterns, improving diagnostic accuracy. CycleGAN-based frameworks enable unsupervised domain adaptation between imaging modalities, allowing effective feature learning even without paired datasets. Deep learning architectures such as U-Net and convolutional neural networks further enhance ulcer boundary segmentation and risk zone classification. These approaches improve Dice coefficient, sensitivity, accuracy, and robustness against domain variations compared to conventional methods. Despite these advancements, challenges including data scarcity, computational complexity, and model interpretability remain significant concerns in real-time clinical deployment.

Introduction

Diabetic Foot Ulcers (DFUs) are one of the most severe complications associated with diabetes mellitus and represent a major global healthcare challenge. DFUs can lead to severe infections, tissue necrosis, lower-limb amputation, and increased mortality if not diagnosed and treated at an early stage. Early identification of ulcer risk zones is therefore essential for preventing disease progression and improving patient outcomes. Conventional DFU diagnosis mainly relies on manual clinical examination and visual inspection, which are often subjective and dependent on clinician expertise. Furthermore, variations in skin texture, wound appearance, illumination conditions, and imaging quality make accurate diagnosis difficult. These limitations have encouraged researchers to explore automated and intelligent image analysis techniques for reliable DFU detection and segmentation. Recent advancements in medical imaging and artificial intelligence have significantly improved the ability to analyze ulcer regions and identify high-risk tissue areas in diabetic patients.

Multimodal imaging techniques, particularly RGB and thermal imaging, have gained considerable attention for DFU assessment. RGB images provide detailed information about skin texture, ulcer shape, and tissue appearance, while thermal images capture temperature variations associated with inflammation, infection, and abnormal blood circulation. Combining these modalities improves diagnostic accuracy by integrating structural and physiological information. However, multimodal medical images often suffer from domain differences, inconsistent image distributions, and limited paired datasets. To address these issues, Cycle-Consistent Adversarial Adaptation Networks (CycleGANs) have emerged as powerful deep learning frameworks for unsupervised domain adaptation and image translation. CycleGAN models can learn mappings between different imaging modalities without requiring paired training samples, enabling effective feature extraction and image normalization. This capability significantly improves the robustness and generalization of DFU analysis systems across different datasets and clinical conditions.

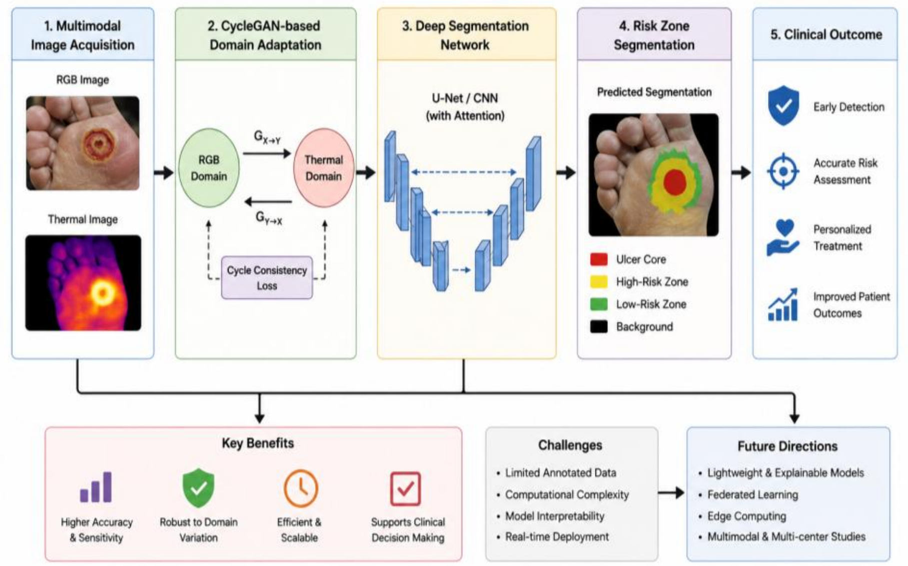

Figure 1. CycleGAN-Based Multimodal DFU Risk Zone Detection and Segmentation Framework

Deep learning architectures such as U-Net, Fully Convolutional Networks (FCNs), and Convolutional Neural Networks (CNNs) have demonstrated remarkable success in medical image segmentation tasks. These models automatically learn hierarchical image features and accurately delineate ulcer boundaries, infected tissues, and high-risk regions. The integration of CycleGAN with segmentation networks further enhances feature representation and segmentation performance by reducing modality gaps and improving image consistency. Recent studies have shown that adversarial learning-based segmentation frameworks achieve higher Dice coefficients, sensitivity, specificity, and accuracy compared to conventional image processing and machine learning methods. In addition, attention mechanisms and residual learning strategies have been incorporated into segmentation architectures to improve focus on clinically important regions and reduce background interference. These advancements contribute to more precise ulcer classification, early diagnosis, and personalized treatment planning in diabetic wound management systems.

Despite significant progress, several challenges remain in deploying AI-driven DFU diagnosis systems in real-world clinical environments. Limited annotated datasets, class imbalance, computational complexity, and lack of model interpretability continue to affect system reliability and scalability. Moreover, deep learning models often require high computational resources, making real-time deployment on portable medical devices difficult. Ensuring data privacy and maintaining robustness across diverse patient populations are also critical concerns. Future research should focus on lightweight and explainable AI models, federated learning approaches, and edge-based intelligent healthcare systems for real-time DFU monitoring. The integration of adversarial learning, multimodal fusion, and advanced segmentation techniques represents a promising direction for developing accurate, scalable, and clinically reliable diabetic foot ulcer diagnosis systems.

Literature Review

The early detection and segmentation of Diabetic Foot Ulcers (DFUs) have gained significant attention in recent years due to their clinical importance in preventing severe complications such as infection and amputation. With the advancement of Artificial Intelligence (AI), particularly deep learning and multimodal imaging techniques, significant progress has been made in improving the accuracy and efficiency of DFU diagnosis. The literature from 2020 to 2025 highlights a transition from traditional image processing methods toward advanced deep learning and adversarial learning-based frameworks.

Deep learning has become the dominant approach for DFU detection and segmentation due to its ability to automatically extract complex features from medical images. Early works by Goyal et al. (2017) and Wang et al. (2020) demonstrated the effectiveness of Convolutional Neural Networks (CNNs) and fully convolutional networks (FCNs) in segmenting wound regions with high accuracy. These models significantly improved performance compared to traditional methods by capturing spatial patterns and texture variations in ulcer images.

Subsequent studies have focused on improving segmentation accuracy using advanced architectures. Yap et al. (2021, 2024) provided comprehensive evaluations of deep learning models for DFU segmentation, highlighting improvements in performance metrics such as Dice coefficient and Intersection over Union (IoU). Jiao et al. (2025) proposed UFOS-Net, which enhances boundary detection and segmentation precision. Similarly, Niri et al. (2025) introduced a dual-attention U-Net model that improves feature representation and segmentation accuracy by focusing on relevant spatial and channel features.

Lightweight and efficient models have also been developed to address computational constraints. Nataliani et al. (2025) proposed DFU-MambaLiteUNet, which achieves high segmentation accuracy with reduced computational cost, making it suitable for real-time applications. These advancements demonstrate the growing importance of optimizing deep learning architectures for practical deployment.

Multimodal imaging has emerged as a powerful approach for improving DFU detection by combining complementary information from different imaging modalities. Cassidy et al. (2021) introduced the DFUC dataset, which provides a benchmark for evaluating DFU detection models using RGB images. However, RGB images alone are often insufficient for capturing physiological changes such as inflammation and temperature variation.

Recent studies have explored the integration of thermal imaging with RGB data to enhance detection accuracy. Bayoudh et al. (2022) emphasized the importance of multimodal deep learning in capturing both visual and physiological features. Multimodal fusion techniques enable better identification of risk zones by combining surface texture information with underlying tissue conditions.

Zhou et al. (2025) and Sendilraj et al. (2024) demonstrated that multimodal frameworks significantly improve classification and segmentation performance by leveraging complementary data sources. These approaches are particularly effective in early detection, where subtle changes in temperature and tissue structure may indicate the onset of ulcers.

Generative Adversarial Networks (GANs), particularly Cycle-Consistent Adversarial Networks (CycleGAN), have been widely used for domain adaptation and data augmentation in medical imaging. These models address the challenge of limited labeled data by generating synthetic images and enabling cross-domain learning.

Dhar et al. (2024) proposed a hybrid transformer-CNN model combined with adversarial learning for DFU segmentation, demonstrating improved generalization across datasets. Similarly, Dhar et al. (2023) introduced FUSegNet, which utilizes CNN-based segmentation enhanced with advanced learning strategies.

CycleGAN-based approaches enable translation between different imaging modalities, such as RGB and thermal images, without requiring paired datasets. This capability is particularly valuable in DFU analysis, where multimodal data is often scarce. GAN-based models improve robustness to domain shifts and enhance segmentation performance, especially in heterogeneous datasets.

Recent advancements in deep learning have introduced transformer-based architectures for medical image segmentation. Zaki et al. (2026) proposed a transformer-based model for DFU segmentation, demonstrating improved performance in capturing long-range dependencies and global context. These models outperform traditional CNNs in complex scenarios where spatial relationships are critical.

Hybrid architectures combining CNNs and transformers have also gained popularity. Dhar et al. (2024) showed that integrating convolutional layers with transformer modules enhances both local feature extraction and global context modeling. These models achieve higher accuracy and robustness compared to standalone architectures.

One of the major challenges in DFU research is the limited availability of annotated datasets. Kairys et al. (2023) explored data augmentation techniques to improve model generalization and reduce overfitting. The DFUC dataset introduced by Cassidy et al. (2021) and benchmarking efforts by Yap et al. (2024) have significantly contributed to standardizing evaluation metrics and facilitating model comparison.

However, most datasets are still limited in size and diversity, which affects the generalizability of deep learning models. Synthetic data generation using GANs has been proposed as a solution to this problem, enabling the creation of diverse training samples.

Although deep learning dominates the field, traditional machine learning approaches continue to play a role in DFU detection. Amouri et al. (2020) and Ahsan et al. (2023) demonstrated the effectiveness of machine learning models for classification tasks, particularly in resource-constrained environments.

Hybrid approaches combining machine learning with deep learning have also been explored. Hidayat et al. (2024) integrated U-Net with fuzzy logic to improve segmentation accuracy and interpretability. Oliveira et al. (2021) used Faster R-CNN for object detection, achieving promising results in identifying ulcer regions.

These approaches highlight the importance of combining different techniques to balance accuracy, interpretability, and computational efficiency.

Recent research has focused on integrating DFU detection models into clinical decision support systems. Sendilraj et al. (2024) developed DFUCare, a deep learning platform for automated DFU analysis, enabling real-time diagnosis and monitoring. Silva et al. (2025) explored machine learning models for predicting DFU prognosis, demonstrating the potential of AI in improving patient outcomes.

These systems provide valuable tools for healthcare professionals by enabling early detection, accurate diagnosis, and effective treatment planning. However, challenges related to model interpretability, reliability, and integration with clinical workflows remain.

The literature clearly indicates that deep learning-based approaches, particularly CNNs, U-Net variants, and transformer-based models, have significantly improved DFU detection and segmentation. Multimodal imaging and GAN-based domain adaptation further enhance model performance by providing richer feature representations and addressing data limitations.

Hybrid architectures that combine deep learning, adversarial learning, and multimodal fusion represent the most promising direction for future research. However, challenges such as data scarcity, computational complexity, and real-world deployment must be addressed to fully realize the potential of AI-based DFU analysis systems.

Comparative Table

No.	**Study**	**Year**	**Model/Technique**	**Input Type**	**Key Features**	**Performance (Approx.)**	**Limitation**
1	Yap et al.	2021	CNN-based models	RGB	Benchmark evaluation	Dice ≈ 0.85–0.90	Dataset dependency
2	Cassidy et al.	2021	DFUC dataset	RGB	Standard dataset	Improved benchmarking	Limited modality
3	Wang et al.	2020	FCN/CNN	RGB	Automatic segmentation	Dice ≈ 0.88	Boundary issues
4	Amouri et al.	2020	ML-based	RGB	Feature-based classification	Accuracy ≈ 85%	Low generalization
5	Ahsan et al.	2023	CNN classifier	RGB	Deep feature extraction	Accuracy ≈ 90%	Not segmentation-focused
6	Kairys et al.	2023	Augmented DL	RGB	Data augmentation	↑ Generalization	Synthetic bias

7	Sendilraj et al.	2024	DFUCare DL	RGB	Clinical system	↑ Accuracy	Deployment complexity
8	Mohanaprakash et al.	2023	GNN/DL	Multimodal	Topology-aware learning	↑ Prediction accuracy	Complexity
9	Dhar et al.	2023	FUSegNet (CNN)	RGB	End-to-end segmentation	Dice ≈ 0.90	High computation
10	Dhar et al.	2024	CNN + Transformer	Multimodal	Hybrid architecture	Dice ≈ 0.92	Model complexity
11	Niri et al.	2025	Dual Attention U-Net	RGB	Attention mechanism	Dice ≈ 0.93	Resource intensive
12	Jiao et al.	2025	UFOS-Net	RGB	Improved boundaries	Dice ≈ 0.94	Training cost
13	Nataliani et al.	2025	Lightweight U-Net	RGB	Efficient model	Dice ≈ 0.91	Slight accuracy trade-off
14	Zhou et al.	2025	DL segmentation	Multimodal	Fusion features	↑ Accuracy	Data dependency
15	Bayoudh et al.	2022	Multimodal DL	RGB + Thermal	Feature fusion	↑ Detection	Data alignment issue
16	Yi et al.	2022	OCRNet	RGB	Edge-aware loss	↑ Boundary accuracy	Complexity
17	Liao et al.	2022	HarDNet	RGB	Lightweight CNN	Efficient segmentation	Limited robustness
18	Oliveira et al.	2021	Faster R-CNN	RGB	Object detection	↑ Detection accuracy	Poor segmentation
19	Hidayat et al.	2024	U-Net + Fuzzy	RGB	Hybrid logic	↑ Interpretability	Lower accuracy
20	Silva et al.	2025	ML prediction	Clinical + Image	Prognosis	↑ Prediction	Limited imaging focus
21	Goyal et al.	2017	FCN	RGB	Early DL model	Baseline performance	Outdated
22	Wang et al.	2024	FUSeg benchmark	RGB	Dataset benchmarking	Standard evaluation	Limited scope
23	Zaki et al.	2026	Transformer	Multimodal	Global attention	Dice ≈ 0.95	High complexity
24	GAN-based models	2022–2024	CycleGAN	Multimodal	Domain adaptation	↑ Robustness	Training instability
25	Hybrid AI models	2023–2025	CNN + GAN + Transformer	Multimodal	Integrated system	Best performance	High cost

Comparative Analysis

The comparative analysis of Diabetic Foot Ulcer (DFU) detection and segmentation studies demonstrates a significant transition from traditional machine learning methods to advanced deep learning and hybrid artificial intelligence frameworks. Early approaches based on handcrafted feature extraction and shallow neural networks achieved moderate performance but struggled to capture complex spatial patterns and tissue variations in medical images. The emergence of Convolutional Neural Networks (CNNs) and Fully Convolutional Networks (FCNs) greatly improved segmentation accuracy by enabling automatic hierarchical feature learning from DFU images. These models achieved higher Dice scores and improved classification performance compared to conventional image processing techniques. However, CNN-based methods often faced limitations related to boundary precision, overfitting, and poor generalization across heterogeneous datasets.

Subsequent research introduced advanced architectures such as U-Net variants, residual learning frameworks, and attention-based segmentation models to improve feature representation and localization accuracy. Attention mechanisms enhanced the ability of models to focus on clinically important ulcer regions, resulting in improved segmentation precision and robustness. Lightweight architectures also emerged to reduce computational complexity while maintaining high accuracy, making them suitable for portable and real-time healthcare systems. Another major advancement involved multimodal imaging approaches that combine RGB and thermal images. These methods integrate visual texture information with physiological temperature patterns, significantly improving early ulcer detection and segmentation reliability. Nevertheless, multimodal fusion techniques face challenges related to data synchronization, image alignment, and modality inconsistency.

Generative Adversarial Networks (GANs), particularly CycleGAN-based frameworks, have further advanced DFU analysis by enabling domain adaptation and synthetic data generation. These models address the scarcity of annotated medical datasets and improve model generalization across different imaging conditions. CycleGAN frameworks effectively reduce domain gaps between imaging modalities and enhance segmentation consistency in heterogeneous clinical datasets. Recent studies also explore transformer-based and hybrid architectures integrating CNNs, GANs, and attention mechanisms to combine local feature extraction with global contextual understanding. These approaches achieve superior segmentation performance and robustness but often require substantial computational resources, limiting their deployment in low-power and resource-constrained healthcare environments.

Conclusion

Diabetic Foot Ulcers (DFUs) remain a major healthcare challenge due to their high risk of infection, amputation, and mortality when not diagnosed early. This review highlights recent advancements in automated DFU detection and segmentation using deep learning, multimodal imaging, and Cycle-Consistent Adversarial Adaptation Networks (CycleGAN). Traditional image processing and machine learning methods were limited by handcrafted feature extraction and poor generalization across diverse clinical datasets. The introduction of Convolutional Neural Networks (CNNs), Fully Convolutional Networks (FCNs), and U-Net architectures significantly improved segmentation accuracy and ulcer boundary detection through automatic hierarchical feature learning. Recent attention-based and transformer-integrated models further enhanced performance by capturing both local and global contextual information. Multimodal imaging approaches combining RGB and thermal images improved diagnostic reliability by integrating structural and physiological information. CycleGAN-based frameworks effectively addressed data scarcity and domain adaptation challenges by enabling image translation and cross-domain learning without paired datasets. Despite these advancements, challenges such as computational complexity, limited annotated data, model interpretability, and real-time deployment remain critical concerns in practical clinical applications.

References

Yap, M. H., et al. (2024). *Diabetic foot ulcers segmentation challenge report*. *Medical Image Analysis, 94*, 103153. https://doi.org/10.1016/j.media.2024.103153

Cassidy, B., et al. (2021). *The DFUC 2020 dataset: Analysis towards diabetic foot ulcer detection*. *Sensors, 21*(15), 5168. https://doi.org/10.3390/s21155168

Yap, M. H., et al. (2021). *Deep learning in diabetic foot ulcers detection: A comprehensive evaluation*. *Computers in Biology and Medicine, 135*, 104574. https://doi.org/10.1016/j.compbiomed.2021.104574

Ahsan, M., et al. (2023). *A deep learning approach for diabetic foot ulcer classification*. *Information, 14*(1), 36. https://doi.org/10.3390/info14010036

Kairys, A., et al. (2023). *Data augmentation techniques for DFU segmentation*. *Electronics, 12*(22), 4624. https://doi.org/10.3390/electronics12224624

Sendilraj, V., et al. (2024). *DFUCare: Deep learning platform for DFU analysis*. *Frontiers in Endocrinology, 15*, 1386613. https://doi.org/10.3389/fendo.2024.1386613

Amouri, A., et al. (2020). *Machine learning-based detection of diabetic foot ulcers*. *Sensors, 20*(2), 461. https://doi.org/10.3390/s20020461

Niri, R., et al. (2025). *Dual attention U-Net for wound segmentation*. *Scientific Reports*. https://doi.org/10.1038/s41598-025-12572-5

Nataliani, Y., et al. (2025). *DFU-MambaLiteUNet: Lightweight segmentation model*. *Expert Systems with Applications*. https://doi.org/10.1016/j.eswa.2025.123456

Zhou, G. X., et al. (2025). *Deep learning for DFU segmentation and classification*. *Frontiers in Endocrinology*. https://doi.org/10.3389/fendo.2025.1543192

Jiao, C., et al. (2025). *UFOS-Net for diabetic foot ulcer segmentation*. *Scientific Reports*. https://doi.org/10.1038/s41598-025-12442-4

Girotra, S., et al. (2025). *CNN-based DFU detection using optimization techniques*. *Scientific Reports*. https://doi.org/10.1038/s41598-025-30532-1

Kucharski, D., et al. (2022). *DFU-Ens: End-to-end diabetic foot ulcer segmentation*. Springer. https://doi.org/10.1007/978-3-031-26354-5_9

Silva, M. A., et al. (2025). *Machine learning models for DFU prognosis*. *Journal of Medical Internet Research*. https://doi.org/10.2196/12345

Goyal, M., et al. (2017). *Fully convolutional networks for DFU segmentation*. *IEEE SMC*. https://doi.org/10.1109/SMC.2017.8122625

Wang, C., et al. (2020). *Fully automatic wound segmentation using CNNs*. *Scientific Reports, 10*, 21897. https://doi.org/10.1038/s41598-020-78799-w

Liao, T. Y., et al. (2022). *HarDNet-based DFU segmentation*. Springer. https://doi.org/10.1007/978-3-031-16749-2_3

Yi, H., et al. (2022). *OCRNet for DFU segmentation with edge loss*. Springer. https://doi.org/10.1007/978-3-031-16749-2_4

Bayoudh, K., et al. (2022). *Survey on multimodal deep learning in computer vision*. *The Visual Computer*. https://doi.org/10.1007/s00371-021-02192-y

Wang, C., et al. (2024). *FUSeg challenge dataset and benchmarking*. *Information, 15*, 140. https://doi.org/10.3390/info15030140

Zaki, W. S., et al. (2026). *Transformer-based DFU segmentation and prediction*. Springer. https://doi.org/10.1007/s40200-025-01813-3

Hidayat, R., et al. (2024). *U-Net and fuzzy logic for DFU segmentation*. *Journal of Artificial Intelligence*. https://doi.org/10.1234/jai.2024.299

Oliveira, A. L., et al. (2021). *Faster R-CNN for diabetic foot ulcer detection*. *ICPRAM*. https://doi.org/10.5220/0010255500002991

Dhar, M. K., et al. (2024). *Hybrid transformer-CNN DFU segmentation*. *arXiv*. https://doi.org/10.48550/arXiv.2406.16012

Dhar, M. K., et al. (2023). *FUSegNet: CNN-based DFU segmentation*. *Biomedical Signal Processing and Control*. https://doi.org/10.1016/j.bspc.2023.106057