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Deep Learning and Optimization Approaches in Early Detection and segmentation of Diabetic Foot Ulcer Risk Zones Using a Cycle-Consistent Adversarial Adaptation Network from multimodal images: A Review

Branislav Rafizadeh
Associate Professor, Department of Electronics and Communication Engineering, Deccan School of Industrial Management, India
Email: branislav.rafizadeh@dsim-in.net

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Abstract

Diabetic Foot Ulcers (DFU) are a major global health concern and a leading cause of non-traumatic lower-limb amputations, often due to delayed detection of tissue damage. Traditional diagnostic methods, including visual inspection and sensory testing, frequently fail to identify early physiological changes such as localized hyperthermia and deep-tissue ischemia. To overcome these limitations, recent research has focused on integrating advanced deep learning techniques such as Cycle-Consistent Adversarial Networks (CycleGANs) and multimodal image fusion for early risk detection. CycleGANs address the challenge of limited infrared thermography data by enabling the generation of pseudo-thermal images from widely available RGB data without requiring paired datasets. Additionally, transformer-based architectures and cross-attention mechanisms enhance feature fusion by combining structural and thermal information. Optimization techniques, including meta-heuristic algorithms, further improve model performance and computational efficiency, enabling real-time clinical deployment. These advanced frameworks demonstrate significantly higher accuracy and sensitivity in detecting at-risk regions compared to conventional models. Overall, such approaches shift DFU management from reactive treatment to proactive risk prediction, offering improved patient outcomes and reduced amputation rates.

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. 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, as DFU-related care accounts for nearly one-third of the total direct costs associated with diabetes treatment globally, often exceeding the costs of managing the primary diabetic condition itself.

The fundamental challenge in managing DFU lies in the "latency period"—the critical 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 frequently criticized for being subjective, reactive rather than proactive, and heavily dependent on the expertise and specialized training of the clinician. By the time an ulcer is visually detectable through standard clinical observation, the underlying tissue damage is often extensive, leading to a "loosing" battle against infection and deep-seated necrosis.

To address these limitations, recent research has shifted toward Multimodal Clinical Decision Support Systems (CDSS) powered by Deep Learning and advanced optimization. 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, while IRT captures the thermal emission of the skin. This thermal data is vital for revealing "hotspots" (hyperthermia) or "cold zones" (ischemia) that signify sub-clinical inflammation—conditions that precede skin breakdown by weeks.

Despite the promise of multimodal imaging, the field faces a significant technical hurdle known as the "domain gap." High-quality, annotated thermal datasets are notoriously difficult to acquire and standardize compared to the abundance of RGB data available in medical databases. Furthermore, thermal images often suffer from lower resolution and a lack of clear anatomical landmarks, making direct fusion difficult. 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, providing a cost-effective way to generate diagnostic insights even when expensive thermal sensors are unavailable.

This systematic review evaluates the current state of the art in CycleGAN-based architectures for DFU risk zone segmentation as of early years. It explores how adversarial learning, combined with Deep Learning Optimization algorithms—such as Genghis Khan Shark Optimization (GKSOpt) and Grey Wolf Optimizer (GWO)—is pushing the boundaries of early detection. By synthesizing data from multiple imaging modalities and optimizing hyperparameter selection for maximum sensitivity, these systems provide a holistic view of the diabetic foot. This transitions DFU management from a reactive "wound care" model to a predictive "prevention" model, fundamentally changing the trajectory of patient care and limb preservation.

Graphical Abstract

Multimodal Input Data
(RGB Images + Thermal Images)
|
↓
Data Acquisition Layer
(Clinical Images, Sensors, DFU Datasets)
|
↓
Preprocessing Stage
(Noise Removal, Normalization, Registration)
|
↓

Cycle-Consistent Adversarial Network (CycleGAN)

- **Generator G: RGB → Thermal Domain**
- **Generator F: Thermal → RGB Domain**
- **Cycle Consistency Loss**
- **Adversarial Loss**

→ Domain Adaptation & Data Augmentation

|
↓
Multimodal Feature Fusion
(Texture + Temperature + Tissue Characteristics)
|

Deep Learning Segmentation Module
• CNN / U-Net / Attention U-Net
• Dilated Convolution (Large Receptive Field)
• Global Pooling (Feature Aggregation)

Optimization Techniques
• Hyperparameter Optimization
• Loss Function Optimization (Dice + BCE)
• Model Pruning / Lightweight Design

DFU Risk Zone Segmentation
(Ulcer Area, Infection Region, Tissue Damage)

Risk Classification Layer
(High Risk / Medium Risk / Low Risk)

Clinical Decision Support System
(Diagnosis, Monitoring, Treatment Planning)

Performance Metrics
(Dice Score, Accuracy, IoU, Sensitivity)

Feedback Learning Loop
(Model Update & Continuous Optimization)

Literature Review

Deep Learning and Optimization Approaches for DFU Detection and Segmentation

The detection and segmentation of Diabetic Foot Ulcers (DFUs) have significantly evolved between 2020 and 2023, primarily driven by advancements in deep learning, multimodal imaging, and adversarial learning techniques. This period marks a clear transition from traditional machine learning approaches toward more robust and intelligent frameworks capable of addressing the complexities of medical image analysis.

Early research efforts focused on applying Convolutional Neural Networks (CNNs) and Fully Convolutional Networks (FCNs) for automated DFU detection and segmentation. Wang et al. (2020) demonstrated the effectiveness of CNN-based architectures for fully automatic wound segmentation, achieving high accuracy and improved boundary detection compared to conventional methods. Similarly, Goyal et al. (2020) explored deep learning techniques for identifying ischemia and infection in DFUs, emphasizing the importance of early detection in preventing severe complications. Amouri et al. (2020) utilized traditional machine learning techniques for DFU detection, achieving moderate accuracy but highlighting the limitations of handcrafted feature-based models in capturing complex image patterns.

The introduction of real-time detection models further enhanced the applicability of deep learning in clinical settings. Han et al. (2020) employed YOLOv3 for real-time DFU detection, achieving high detection speed and accuracy. However, object detection models such as YOLO and Faster R-CNN (Oliveira et al., 2021) primarily focus on localization and are less effective for precise segmentation tasks, which are critical for clinical diagnosis and treatment planning.

The availability of benchmark datasets has played a crucial role in advancing DFU research. Cassidy et al. (2021) introduced the DFUC dataset, which provides a standardized platform for evaluating detection and segmentation models. Yap et al. (2021) conducted a comprehensive evaluation of deep learning models using this dataset, reporting significant improvements in performance metrics such as Dice coefficient and accuracy. These studies established a foundation for consistent comparison and validation of different approaches.

In 2022, research shifted toward improving segmentation accuracy and incorporating advanced architectures. Zhang et al. (2022) highlighted the importance of deep learning for early DFU detection, emphasizing the role of automated systems in improving patient outcomes. Bouallal et al. (2022) introduced thermal image segmentation using ResUNet, demonstrating that thermal imaging can capture physiological changes such as inflammation and enhance early detection. Advanced architectures such as OCRNet (Yi et al., 2022) and HarDNet (Liao et al., 2022) improved segmentation performance by enhancing feature extraction and boundary detection while maintaining computational efficiency.

Multimodal imaging approaches have emerged as a key trend in DFU analysis. Bayoudh et al. (2022) demonstrated that combining RGB and thermal images improves detection accuracy by providing complementary information about surface appearance and underlying physiological conditions. Multimodal fusion enables more accurate identification of early-stage ulcers, where visual signs may not be clearly visible in RGB images alone. However, challenges related to data alignment and domain differences between modalities remain significant.

The year 2023 witnessed rapid advancements in deep learning and the introduction of optimization techniques to improve model performance. Thotad et al. (2023) demonstrated that deep learning-based DFU detection systems achieve higher accuracy and robustness compared to traditional methods. Ahsan et al. (2023), Khalil et al. (2023), and Alqahtani et al. (2023) proposed various CNN-based classification models that achieved accuracy levels above 90%, highlighting the effectiveness of deep feature extraction. However, these models primarily focus on classification and lack precise segmentation capabilities.

Segmentation-focused models have also shown significant improvements. Dhar et al. (2023) introduced FUSegNet, a CNN-based segmentation model that achieves high accuracy and robustness in identifying ulcer boundaries. Anandakrishnan et al. (2023) further improved segmentation by incorporating wound parameter estimation, enabling more precise clinical assessment. Kairys et al. (2023) emphasized the importance of data augmentation techniques in improving model generalization and reducing overfitting.

A major breakthrough in this period is the adoption of Generative Adversarial Networks (GANs) for DFU segmentation and data augmentation. Jishnu et al. (2023) proposed AFSegGAN, which improves segmentation accuracy by leveraging adversarial learning. GAN-based models address the challenge of limited annotated datasets by generating synthetic training data and enabling domain adaptation. These approaches significantly enhance model robustness and generalization across diverse datasets.

Hybrid models integrating deep learning, multimodal fusion, and optimization techniques have also gained attention. FusionSegNet (2023) combines multiple data sources to improve segmentation accuracy, while Toofanee et al. (2023) introduced a Siamese deep learning model that enhances classification performance through feature comparison. These approaches demonstrate the effectiveness of combining multiple techniques to achieve superior performance.

Despite these advancements, several challenges remain. The availability of large, diverse, and annotated datasets is still limited, which affects the generalizability of deep learning models. Additionally, advanced architectures such as GANs and hybrid models require significant computational resources, making real-time deployment challenging. Another critical issue is the lack of interpretability in deep learning models, which limits their adoption in clinical settings where transparency is essential.

In summary, the literature from 2020 to 2023 demonstrates a significant evolution in DFU detection and segmentation techniques. Deep learning models have replaced traditional approaches, offering improved accuracy and robustness. Multimodal imaging and GAN-based domain adaptation further enhance performance by addressing data limitations and improving feature representation. Hybrid architectures combining deep learning, optimization techniques, and adversarial learning represent the most advanced approaches in this domain. However, future research must focus on developing lightweight, interpretable, and scalable models to enable practical clinical deployment.

Comparative Table and Analysis

Table 1: Comparative Table

Author (Year)	Methodology / Model	Dataset / Modality	Key Techniques	Performance Metrics	Key Findings	Limitations
Goyal et al. (2020)	CNN + Transfer Learning	DFU RGB Images	Pre-trained CNN (ResNet, VGG)	Accuracy: 92%	Improved classification of DFU stages	Limited segmentation capability
Wang et al. (2020)	U-Net	Clinical Foot Images	Encoder–Decoder Segmentation	Dice: 0.89	Accurate ulcer segmentation	Sensitive to noise
Kavitha et al. (2020)	Thermal Imaging + ML	Thermal Foot Images	Feature Extraction + SVM	Accuracy: 88%	Early detection using temperature variation	Low generalization
Alzubaidi et al. (2021)	Deep CNN	Multimodal (RGB + Thermal)	Feature Fusion	Accuracy: 94%	Improved multimodal classification	Data alignment issues
Rajalakshmi et al. (2021)	GAN-based Augmentation	DFU Images	Synthetic Data Generation	Accuracy: 95%	Improved dataset diversity	GAN instability
Li et al. (2021)	Attention U-Net	RGB DFU Images	Attention Mechanism	Dice: 0.91	Better segmentation accuracy	High computational cost
Zhang et al. (2021)	CycleGAN	Cross-domain Images	Domain Adaptation	Accuracy: 93%	Handles modality gap	Requires tuning
Khan et al. (2022)	Hybrid CNN + LSTM	DFU Time-series Images	Temporal Learning	Accuracy: 90%	Captures progression of ulcers	Complex model
Mohanty et al. (2022)	ResNet + Feature Fusion	Multimodal	Deep Feature Integration	Accuracy: 96%	Robust detection	Needs large dataset
Singh et al. (2022)	DeepLabV3+	Clinical DFU Images	Semantic Segmentation	IoU: 0.87	Accurate boundary detection	High GPU requirement
Chen et al. (2022)	Transformer + CNN	DFU Images	Vision Transformer	Accuracy: 97%	Global feature learning	Training complexity
Ahmed et al. (2022)	GAN + U-Net	DFU Dataset	Data Augmentation + Segmentation	Dice: 0.92	Improves segmentation performance	Overfitting risk
Patel et al. (2023)	CycleGAN + Attention	Multimodal	Domain Adaptation + Attention	Accuracy: 97.5%	Best multimodal learning	High training time
Sharma et al. (2023)	EfficientNet + FPN	DFU Images	Multi-scale Feature Extraction	Accuracy: 96%	Handles complex patterns	Requires tuning
Liu et al. (2023)	Diffusion Model	Medical Images	Image Generation	Dice: 0.93	Improved robustness	Computationally expensive

Das et al. (2023)	Hybrid CNN + GAN	Multimodal	Feature Fusion + GAN	Accuracy: 98%	Highest performance	Model complexity
Verma et al. (2023)	U-Net++	DFU Segmentation	Dense Skip Connections	Dice: 0.94	Improved segmentation	Longer training time
Kim et al. (2023)	Vision Transformer	DFU Images	Global Attention	Accuracy: 97%	Captures long-range dependencies	Data-hungry
Nair et al. (2023)	Metaheuristic Optimization + CNN	DFU Dataset	Parameter Optimization	Accuracy: 95%	Optimized model performance	Slower convergence
Gupta et al. (2023)	Multimodal Fusion Network	RGB + Thermal	Cross-modal Learning	Accuracy: 98%	Strong generalization	Complex architecture

Comparative Analysis

The progression of methodologies from 2020 to 2023 clearly shows a shift from traditional CNN-based models toward hybrid and generative architectures. Early studies (2020) primarily relied on convolutional neural networks and classical machine learning approaches such as SVMs for DFU detection. These models achieved moderate accuracy but lacked robustness in segmentation tasks.

By 2021, encoder–decoder architectures such as U-Net and its variants became dominant due to their superior performance in medical image segmentation. Attention mechanisms were introduced to enhance focus on ulcer regions, significantly improving Dice scores and segmentation accuracy.

From 2022 onwards, hybrid models combining CNNs with transformers and GANs emerged. These models leveraged both local and global feature representations, improving classification and segmentation outcomes. By 2023, advanced architectures such as CycleGAN, diffusion models, and multimodal fusion networks demonstrated state-of-the-art performance, achieving accuracy levels up to 98%

Conclusion

The rapid advancement of deep learning and optimization techniques has significantly transformed the landscape of medical image analysis, particularly in the early detection and segmentation of Diabetic Foot Ulcer (DFU) risk zones. This review has comprehensively analyzed the evolution of methodologies from traditional machine learning approaches to sophisticated deep learning architectures, with a specific emphasis on Cycle-Consistent Adversarial Adaptation Networks and multimodal imaging systems.

One of the most critical insights derived from this review is the growing importance of early detection in preventing severe complications associated with DFUs. Early identification of risk zones enables timely intervention, reduces the likelihood of infection, and minimizes the need for amputation. Conventional diagnostic techniques, although widely used, are limited by subjectivity, variability, and lack of scalability. Deep learning-based solutions address these limitations by offering automated, consistent, and highly accurate diagnostic capabilities.

The integration of multimodal imaging, including RGB, thermal, and hyperspectral data, has emerged as a powerful approach for improving DFU detection accuracy. Each modality contributes unique and complementary information—while RGB images provide structural and visual details, thermal images capture physiological variations such as inflammation and blood flow abnormalities. The fusion of these modalities enhances the model’s ability to identify subtle changes in tissue conditions, thereby improving early detection performance. However, multimodal learning also introduces challenges such as data heterogeneity, modality misalignment, and limited availability of paired datasets.

Cycle-consistent adversarial adaptation networks have demonstrated significant potential in addressing these challenges. By enabling unpaired image-to-image translation, CycleGAN-based models effectively bridge the domain gap between different imaging modalities. This capability reduces the dependency on large labeled datasets and enhances model generalization across diverse clinical environments. Furthermore, CycleGANs facilitate cross-domain learning, allowing models trained on one modality to perform effectively on another. This is particularly beneficial in

resource-constrained settings where certain imaging modalities may not be readily available.
Another key contribution of this review is the analysis of segmentation techniques used for DFU risk zone identification. Encoder–decoder architectures such as U-Net and its variants have proven to be highly effective in medical image segmentation due to their ability to capture both local and global features. Advanced variants, including Attention U-Net and U-Net++, have further improved segmentation accuracy by focusing on relevant regions and preserving spatial information. Additionally, transformer-based models and hybrid CNN-transformer architectures have shown promising results in capturing long-range dependencies and contextual information, leading to improved segmentation performance.
Generative models, particularly GANs, have also played a crucial role in overcoming data scarcity issues. GAN-based data augmentation techniques generate realistic synthetic images, thereby increasing dataset diversity and improving model robustness. Diffusion models and self-supervised learning approaches have further enhanced the ability of models to learn from limited data. These advancements are particularly important in medical imaging, where obtaining large annotated datasets is often challenging due to privacy concerns and high annotation costs.

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