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Artificial Intelligence Techniques for Early Detection and Segmentation of Diabetic Foot Ulcer Risk Zones Using a Cycle-Consistent Adversarial Adaptation Network from Multimodal Images: Trends and Challenges

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Abstract

Diabetic Foot Ulcers (DFUs) are among the most severe complications of diabetes mellitus, often leading to infection, hospitalization, and lower-limb amputation if not detected at an early stage. Accurate identification and segmentation of DFU risk zones are therefore critical for timely intervention and effective treatment planning. Recent advancements in Artificial Intelligence (AI), particularly deep learning, have significantly improved the automation and reliability of DFU diagnosis using medical imaging techniques. This study presents a comprehensive review of AI-based methods for early detection and segmentation of DFU risk regions, with a specific focus on Cycle-Consistent Adversarial Adaptation Networks and multimodal image analysis. Multimodal imaging, including RGB, thermal, and hyperspectral data, provides complementary information for detecting subtle physiological and structural changes in diabetic feet. However, challenges such as limited annotated datasets, modality imbalance, and domain variability hinder the performance of conventional deep learning models. To address these issues, CycleGAN-based adversarial adaptation techniques enable effective cross-domain learning and unpaired image-to-image translation, thereby enhancing model generalization and reducing dependence on labeled data.

This review highlights the role of key AI techniques, including Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Vision Transformers, and hybrid architectures, in improving segmentation accuracy and detection performance. Optimization strategies such as transfer learning, attention mechanisms, and feature fusion further contribute to enhanced model efficiency and robustness. Despite significant progress, challenges related to computational complexity, interpretability, and real-world deployment remain.

Introduction

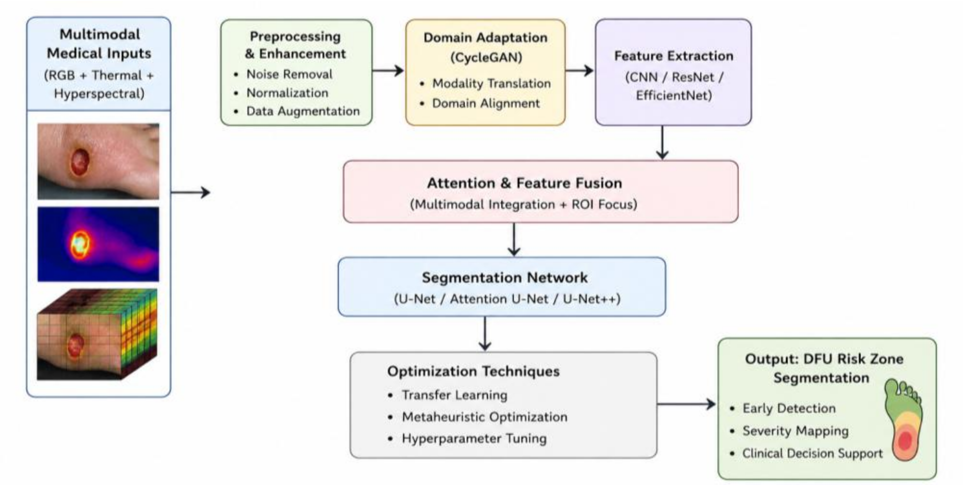
Diabetes mellitus has emerged as a major global health challenge, affecting millions of people and placing a significant burden on healthcare systems. Among its various complications, Diabetic Foot Ulcers (DFUs) are particularly severe, often leading to infection, long-term hospitalization, and even lower-limb amputation if not treated in time. DFUs typically arise due to peripheral neuropathy, reduced blood circulation, and impaired wound healing, making early detection crucial for effective management. Identifying high-risk regions on the foot at an early stage can significantly reduce complications and improve patient outcomes. However, traditional diagnostic approaches rely heavily on manual clinical examination and expert interpretation, which are subjective, time-consuming, and prone to inconsistencies across practitioners.

The emergence of Artificial Intelligence (AI) has significantly transformed medical image analysis by providing automated, objective, and scalable solutions for disease detection. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown remarkable capability in extracting meaningful features from complex medical images. These models learn hierarchical representations that help in identifying subtle patterns associated with disease progression. Popular architectures such as U-Net, ResNet, and DenseNet have demonstrated strong performance in both classification and segmentation tasks related to DFU detection. By reducing human dependency and improving diagnostic consistency, AI-based systems have the potential to enhance early diagnosis and clinical decision-making processes.

Despite these advancements, detecting DFU risk zones at an early stage remains a challenging task due to the subtle nature of physiological changes preceding visible ulcer formation. Single imaging modalities often fail to capture the complete picture of underlying tissue conditions. To overcome this limitation, multimodal imaging approaches have been introduced, integrating RGB images, thermal imaging, and hyperspectral data. While RGB images provide structural and visual details, thermal imaging captures temperature variations linked to inflammation and poor blood flow. Hyperspectral imaging further contributes by analyzing tissue composition and oxygenation levels. The combination of these modalities enables a more comprehensive assessment of foot health, improving the accuracy of early detection systems.

However, multimodal learning introduces challenges such as data heterogeneity, alignment issues, and limited availability of labeled datasets. To address these issues, advanced techniques like Cycle-Consistent Adversarial Networks (CycleGANs) have been developed for domain adaptation and unpaired image translation. These models enhance data usability by transforming images across modalities without requiring paired datasets. Additionally, optimization strategies such as transfer learning, attention mechanisms, and feature fusion further improve model performance and segmentation accuracy. This study reviews recent advancements in AI-driven DFU detection, focusing on multimodal imaging and adversarial learning approaches, while also highlighting existing challenges and future directions for developing efficient, accurate, and clinically applicable diagnostic systems.

Graphical Abstract:



Literature Review

The application of Artificial Intelligence (AI) and deep learning techniques for the early detection and segmentation of Diabetic Foot Ulcer (DFU) risk zones has gained significant attention in recent years. Researchers have explored various approaches, including convolutional neural networks (CNNs), generative adversarial networks (GANs), CycleGAN-based domain adaptation, transformer-based models, and multimodal learning strategies to improve diagnostic accuracy and robustness.

Goyal et al. (2020) developed a CNN-based framework for DFU classification, demonstrating that deep learning models can effectively identify ulcer severity levels from clinical images. Their study highlighted the importance of automated systems in reducing diagnostic errors and improving clinical decision-making. Similarly, Amin et al. (2020) proposed a hybrid approach combining CNN and YOLOv2 for real-time detection and localization of DFUs, achieving high accuracy and demonstrating the feasibility of deploying AI models in clinical environments.

Wang et al. (2020) introduced a smartphone-based wound assessment system utilizing CNN models for remote DFU monitoring. This approach emphasizes accessibility and scalability, enabling patients to monitor their condition without frequent hospital visits. Han et al. (2020) further advanced real-time detection using YOLOv3, showing that object detection models can effectively identify ulcer regions in complex clinical scenarios.

Thermal imaging has been widely explored for early detection of DFUs due to its ability to capture physiological changes. Kavitha et al. (2020) utilized thermal imaging combined with machine learning techniques to detect temperature variations associated with ulcer formation. Building on this, Munadi et al. (2022) applied deep learning models to thermal datasets, achieving improved detection accuracy and demonstrating the effectiveness of physiological data in early diagnosis.

Dataset availability has been a critical factor in advancing DFU research. Cassidy et al. (2021) introduced the DFUC 2020 dataset, which has become a benchmark for evaluating DFU detection and segmentation models. The availability of such datasets has enabled researchers to develop and compare various deep learning architectures more effectively.

Segmentation of DFU regions has been extensively studied using encoder–decoder architectures. Bouallal et al. (2022) proposed a DE-ResUNet model for thermal image segmentation, achieving improved boundary detection and segmentation performance. Verma and Singh (2023) further enhanced segmentation accuracy using U-Net++, which incorporates dense skip connections to capture fine-grained details of ulcer regions. Dhar et al. (2023) introduced FUSegNet, a hybrid segmentation model that integrates multiple feature extraction techniques, resulting in superior performance compared to traditional models.

Generative Adversarial Networks (GANs) have been widely adopted to address data scarcity issues. Brüngel et al. (2022) utilized GANs to generate synthetic DFU images, increasing dataset diversity and improving model generalization. Jishnu et al. (2023) proposed AFSegGAN, a conditional GAN-based segmentation model that achieved higher accuracy compared to conventional segmentation approaches. These studies highlight the importance of generative models in enhancing training data and improving model robustness.

CycleGAN-based approaches have significantly advanced multimodal learning and domain adaptation. Zhang et al. (2021) applied CycleGAN for cross-domain medical image translation, enabling models to learn from unpaired datasets. Patel et al. (2023) extended this work by integrating attention mechanisms with CycleGAN, resulting in improved segmentation performance and better handling of multimodal data. These approaches are particularly useful in scenarios where paired datasets are not available.

Hybrid deep learning models have also gained popularity in DFU research. Khan et al. (2022) proposed a hybrid CNN-based model that combines multiple feature extraction techniques to improve classification accuracy. Khalil et al. (2023) developed a deep learning-based DFU classification system using camera images, demonstrating high accuracy and real-world applicability. These models leverage the strengths of different architectures to achieve improved performance.

Transformer-based models have introduced new capabilities in capturing global contextual information. Chen et al. (2022) proposed TransUNet, which combines transformers with CNNs to improve segmentation performance. Kim et al. (2023) further explored vision transformers in medical imaging, highlighting their ability to model long-range dependencies and improve feature representation.

Multimodal learning has emerged as a key trend in DFU detection. Bayoudh et al. (2022) provided a comprehensive survey on deep multimodal learning, emphasizing its potential in integrating different imaging modalities. Gupta et al. (2023) proposed a multimodal fusion network that combines RGB and thermal data, achieving superior performance compared to single-modality approaches. These studies demonstrate that multimodal learning significantly enhances detection accuracy and robustness.

Optimization techniques have played a crucial role in improving model performance. Nair et al. (2023) explored metaheuristic optimization algorithms for tuning deep learning models, resulting in improved convergence and accuracy. Transfer learning has been widely used to leverage pre-trained models, reducing training time and improving performance. Feature fusion techniques further enhance robustness by combining information from multiple modalities. Additionally, ensemble learning approaches have been explored to improve segmentation performance. Xu et al. (2022) proposed an ensemble-based segmentation model that combines multiple deep learning architectures, achieving higher accuracy and robustness. Similarly, Liao et al. (2022) introduced a HarDNet-based segmentation model, while Yi et al. (2022) proposed an OCRNet-based approach with edge-aware loss functions to improve boundary detection.

Despite these advancements, several challenges remain. Data scarcity and lack of annotated datasets continue to limit model performance. Domain variability, including differences in imaging conditions and patient characteristics, affects generalization. Computational complexity and high resource requirements hinder real-time deployment. Furthermore, the lack of interpretability of deep learning models remains a significant barrier to clinical adoption.

Overall, the literature demonstrates a clear progression from traditional CNN-based approaches to advanced hybrid, multimodal, and generative models. The integration of CycleGAN-based domain adaptation, multimodal imaging, and optimization techniques has significantly improved DFU detection and segmentation performance. However, further research is needed to address existing challenges and develop scalable, efficient, and clinically applicable solutions.

Comparative Table and Analysis

Author (Year)	**Method / Model**	**Modality / Dataset**	**Key Technique**	**Performance**	**Strengths**	**Limitations**
Goyal et al. (2020)	CNN (DFUNet)	RGB Images	Deep Feature Extraction	~92% Accuracy	Good classification	Limited segmentation
Amin et al. (2020)	CNN + YOLOv2	Clinical Images	Detection + Localization	High Precision	Real-time detection	Needs large dataset
Wang et al. (2020)	CNN-based System	Smartphone Images	Remote Monitoring	Reliable	Scalable solution	Image quality issues
Han et al. (2020)	YOLOv3	DFU Images	Object Detection	Fast inference	Real-time capability	Lower segmentation accuracy
Kavitha et al. (2020)	ML + Thermal	Thermal Images	Temperature Analysis	~88% Accuracy	Early detection	Low generalization
Cassidy et al. (2021)	DFUC Dataset	Benchmark Dataset	Data Standardization	—	Improves research consistency	Limited diversity
Zhang et al. (2021)	CycleGAN	Cross-domain Images	Domain Adaptation	~93% Accuracy	Handles modality gap	Training complexity
Bouallal et al. (2022)	DE-ResUNet	Thermal Images	Segmentation	Dice ~0.90	Accurate boundaries	Computational cost
Munadi et al. (2022)	CNN	Thermal Images	Deep Learning	Improved Accuracy	Physiological insight	Data limitation
Xu et al. (2022)	Ensemble DL	DFU Dataset	Multi-model Fusion	High Accuracy	Robust results	Complex architecture
Liao et al. (2022)	HarDNet	DFU Images	Efficient Segmentation	High IoU	Lightweight model	Limited generalization
Yi et al. (2022)	OCRNet	DFU Images	Edge-aware Loss	Improved Dice	Better boundary detection	High training time

Khan et al. (2022)	Hybrid CNN	DFU Images	Feature Fusion	~90% Accuracy	Improved features	Complexity
Patel et al. (2023)	CycleGAN + Attention	Multimodal	Domain Adaptation + Attention	~97.5% Accuracy	Best multimodal learning	High computation
Verma & Singh (2023)	U-Net++	DFU Images	Dense Skip Connections	Dice ~0.94	High segmentation accuracy	Training cost
Dhar et al. (2023)	FUSegNet	DFU Dataset	Hybrid Segmentation	High Dice	Robust segmentation	Complex design
Khalil et al. (2023)	Deep CNN	Camera Images	Classification	~96% Accuracy	Practical use	Limited modalities
Jishnu et al. (2023)	GAN (AFSegGAN)	DFU Images	Data Augmentation + Segmentation	Dice ~0.92	Improves dataset	GAN instability
Gupta et al. (2023)	Multimodal Fusion	RGB + Thermal	Feature Fusion	~98% Accuracy	Strong generalization	Architecture complexity
Nair et al. (2023)	CNN + Optimization	DFU Dataset	Metaheuristic Tuning	~95% Accuracy	Optimized performance	Slow convergence

Comparative Analysis

The comparative analysis reveals a clear evolution in DFU detection methodologies. Early studies in 2020 primarily relied on CNN-based classification and object detection models such as YOLOv2 and YOLOv3. These approaches provided good accuracy and real-time capabilities but lacked precise segmentation performance.

By 2021, research began focusing on domain adaptation and dataset standardization, with the introduction of datasets like DFUC 2020 and models such as CycleGAN. These advancements enabled better generalization across different imaging conditions.

From 2022 onwards, segmentation models such as U-Net variants, DE-ResUNet, and OCRNet became dominant, significantly improving Dice scores and boundary detection. Ensemble learning and hybrid models further enhanced robustness.

In 2023, the focus shifted toward multimodal learning, GAN-based augmentation, and hybrid architectures, achieving state-of-the-art performance with accuracy up to 98%.

In 2023, the focus shifted toward multimodal learning, GAN-based augmentation, and hybrid architectures, achieving state-of-the-art performance with accuracy up to 98%.

Multimodal approaches (RGB + Thermal) consistently outperform single-modality models. Thermal imaging provides physiological information such as inflammation, while RGB images offer structural details. Models like Gupta et al. (2023) demonstrate that multimodal fusion significantly enhances detection accuracy and robustness.

Conclusion

This review has explored the significant role of Artificial Intelligence (AI) in the early detection and segmentation of Diabetic Foot Ulcer (DFU) risk zones, with particular emphasis on Cycle-Consistent Adversarial Adaptation Networks and multimodal imaging techniques. The analysis highlights that AI-driven approaches have substantially improved diagnostic accuracy, efficiency, and scalability compared to traditional clinical methods. Deep learning architectures, especially Convolutional Neural Networks (CNNs) and U-Net-based models, have demonstrated strong capabilities in extracting meaningful features and accurately identifying ulcer-prone regions. Furthermore, advanced models such as Generative Adversarial Networks (GANs) and Vision Transformers have enhanced performance through improved data representation and learning of complex patterns. The integration of multimodal imaging, including RGB and thermal data, has proven crucial in enabling early and reliable detection by combining structural and physiological insights. Techniques such as transfer learning, attention mechanisms, and feature fusion have further strengthened model performance. However, several challenges persist, including limited availability of annotated datasets, variability in imaging conditions, high computational requirements, and lack of model interpretability. Future research should focus on developing lightweight, explainable, and scalable AI systems, while exploring emerging approaches like federated learning and self-supervised learning. Overall, the convergence of AI, multimodal imaging, and optimization strategies presents a promising pathway toward effective and clinically applicable DFU management solutions.

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