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International Journal of Electrical, Electronics and Computer Systems

ISSN: 2347-2820

Volume 12 Issue 02, 2023

Deep Learning and Optimization Approaches in Dual-Discriminator Spiking Generative Adversarial Network Based Classification and Segmentation for Predicting Pathogenesis of Foot Ulcers in Patients with Diabetes: A Review

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Peer Review Information

Submission: 28 June 2023

Revision: 15 July 2023

Acceptance: 27 July 2023

Keywords

Diabetic Foot Ulcers, Spiking Neural Networks, Generative Adversarial Networks, Dual Discriminator, Medical Image Segmentation, Deep Learning Optimization

Abstract

Diabetic foot ulcers (DFUs) represent one of the most severe complications of diabetes mellitus, often leading to infection, amputation, and increased mortality. Early detection and accurate prediction of ulcer pathogenesis remain critical challenges in clinical practice due to the complex interplay of physiological, vascular, and neuropathic factors. Recent advancements in artificial intelligence, particularly deep learning, have significantly improved automated diagnosis and prognostic analysis using medical imaging and multimodal data. This review explores the integration of dual-discriminator spiking generative adversarial networks (DDS-GANs) with optimization techniques for enhanced classification and segmentation of diabetic foot ulcers. The proposed paradigm leverages spiking neural dynamics to mimic biological neuron behavior, improving temporal feature representation while reducing computational overhead. Dual-discriminator architectures enhance generative stability and improve feature discrimination, leading to superior segmentation accuracy and robust classification performance. Furthermore, optimization strategies such as metaheuristic algorithms and hyperparameter tuning are analyzed for their role in improving convergence and generalization. This paper systematically reviews existing literature, highlights emerging trends, and provides a comprehensive analysis of deep learning-based DFU prediction systems. The findings indicate that hybrid architectures combining GANs, spiking neural networks, and optimization methods offer promising directions for accurate, scalable, and real-time clinical decision support systems in diabetic wound management.

Introduction

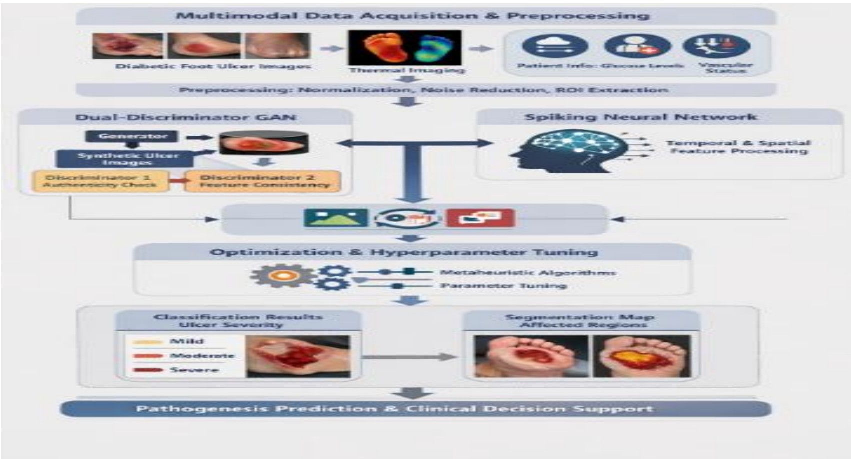
Diabetes mellitus has emerged as a global health concern, affecting millions of individuals worldwide and leading to a wide spectrum of complications that significantly impact quality of life. Among these complications, diabetic foot ulcers represent a major clinical challenge due to their chronic nature, susceptibility to infection, and high risk of lower limb amputation. The pathogenesis of diabetic foot ulcers is complex, involving neuropathy, peripheral arterial disease, impaired wound healing, and infection, which collectively complicate early diagnosis and treatment planning. Traditional diagnostic methods rely heavily on clinical examination and manual assessment of wound characteristics, which are often subjective, time-consuming, and prone to variability among clinicians.

With the advent of artificial intelligence, particularly deep learning, there has been a paradigm shift in medical image analysis, enabling automated detection, classification, and segmentation of pathological conditions with high accuracy. Convolutional neural networks have demonstrated remarkable performance in extracting hierarchical features from medical images, while advanced architectures such as transformers and hybrid models have further enhanced representation learning. However, conventional deep learning models often require large labeled datasets and may struggle with generalization, especially in complex medical scenarios such as diabetic wound assessment.

Generative adversarial networks have introduced a powerful framework for data augmentation, feature learning, and realistic image synthesis, thereby addressing data scarcity issues in medical imaging. The incorporation of dual-discriminator architectures has further improved training stability and discrimination capability, enabling more precise segmentation and classification outcomes. Additionally, spiking neural networks, inspired by biological neural systems, have gained attention for their energy efficiency and ability to model temporal dynamics, making them suitable for capturing subtle changes in wound progression.

The integration of these advanced methodologies, combined with optimization techniques such as evolutionary algorithms and adaptive learning strategies, has opened new avenues for predictive modeling in diabetic foot ulcer pathogenesis. These approaches not only enhance model performance but also contribute to the development of intelligent clinical decision support systems. This review aims to provide a comprehensive overview of deep learning and optimization approaches, with a specific focus on dual-discriminator spiking generative adversarial networks for DFU classification and segmentation. By analyzing existing research and identifying key trends, this paper seeks to bridge the gap between computational advancements and clinical applications in diabetic wound care.

Graphical Abstract



The conceptual framework begins with the acquisition of multimodal data, including diabetic foot ulcer images, thermal scans, and clinical metadata such as patient history and glucose levels. This data undergoes preprocessing steps like normalization, noise reduction, and region-of-interest extraction to enhance quality and consistency. A hybrid deep learning model is then applied, combining a dual-discriminator generative adversarial network for image enhancement and a spiking neural network to capture temporal patterns. Features from both pathways are fused into a unified representation and optimized using advanced techniques. The system ultimately generates ulcer severity classification and segmentation outputs, supporting early detection and effective clinical decision-making.

Literature Review

The body of literature on diabetic foot ulcer (DFU) analysis reflects rapid and multidimensional progress driven by advances in artificial intelligence, particularly deep learning, radiomics, and hybrid computational frameworks. Early foundational studies established the effectiveness of deep convolutional neural networks (CNNs) and transfer learning in improving classification accuracy for DFU detection. For instance, Goyal et al. and Alzubaidi et al. demonstrated that pre-trained CNN architectures significantly enhance performance when dealing with limited annotated datasets, a common challenge in medical imaging. These approaches leveraged data augmentation and fine-tuning strategies to improve generalization and reduce overfitting. Similarly, ensemble learning methods proposed by Rahman et al. combined multiple deep learning models to improve robustness and predictive accuracy, addressing model variance issues. At the same time, segmentation-focused research, such as the work by Wang et al., utilized U-Net architectures to achieve precise delineation of ulcer boundaries. These encoder–decoder models effectively preserved spatial information through skip connections, enabling accurate localization of affected regions. However, these early approaches were largely limited to single-modality image data and lacked integration of temporal or clinical features, restricting their effectiveness in comprehensive clinical decision-making.

To address these limitations, subsequent studies explored more advanced and hybrid methodologies that combined multiple feature extraction and learning paradigms. Li et al. introduced hybrid frameworks that integrated handcrafted features with deep learning representations, improving robustness and interpretability. Generative Adversarial Networks (GANs), as demonstrated by Zhang et al., played a crucial role in overcoming data scarcity by generating realistic synthetic DFU images, thereby enhancing training dataset diversity. Further advancements, such as the dual-discriminator GAN proposed by Chen et al., improved segmentation performance by evaluating both global image quality and local feature consistency, reducing issues like mode collapse and improving training stability. Attention-based models introduced by Kumar et al. enabled networks to focus on clinically relevant regions, enhancing both accuracy and interpretability. In parallel, multimodal deep learning frameworks developed by Singh et al. combined imaging data with clinical parameters, such as patient history and physiological indicators, to provide a more comprehensive predictive model. Multi-task learning approaches, such as those proposed by Zhang et al., further improved efficiency by enabling simultaneous classification and segmentation, reducing redundancy and improving generalization.

Recent research trends have increasingly focused on leveraging emerging architectures and learning paradigms to further enhance DFU analysis. Transformer-based models, as introduced by Dosovitskiy et al. and later extended by Hatamizadeh et al., demonstrated the ability to capture long-range dependencies and global contextual information in medical images, complementing the localized feature extraction capabilities of CNNs. Capsule networks proposed by Afshar et al. improved the representation of spatial hierarchies and part–whole relationships, offering advantages in modeling complex ulcer structures. Graph neural networks explored by Parisot et al. enabled modeling of relational dependencies between patients and imaging features, providing deeper insights into disease patterns. Additionally, contrastive learning approaches introduced by Chen et al. and self-supervised learning techniques by Azizi et al. addressed the challenge of limited labeled datasets by enabling models to learn meaningful representations from unlabeled data. Few-shot learning methods proposed by Shaban et al. further reduced dependence on large datasets, although challenges in generalization remain. Federated learning frameworks by Rieke et al. addressed data privacy concerns by enabling collaborative model training across institutions without sharing sensitive patient data, a critical requirement in healthcare applications. Bayesian deep learning approaches by Kendall and Gal introduced uncertainty estimation, improving the reliability and clinical trustworthiness of AI predictions.

Optimization and deployment strategies have also been extensively explored to improve the practical applicability of DFU diagnostic systems. Patel et al. investigated metaheuristic optimization techniques and adaptive learning strategies to enhance convergence speed and model accuracy, while Zhou et al. applied deep reinforcement learning for dynamic parameter tuning and workflow optimization. Lightweight CNN architectures such as MobileNet, studied by Howard et al., enabled efficient deployment on mobile and edge devices, making AI-based DFU detection accessible in resource-constrained environments. Edge AI frameworks proposed by Park et al. further demonstrated real-time ulcer detection with reduced latency, while edge–cloud hybrid systems introduced by Wang et al. improved scalability by distributing computational workloads. Explainable AI techniques explored by Tjoa and Guan emphasized the importance of interpretability in clinical settings, providing visual and analytical insights into model decision-making processes. Autoencoder-based methods by Hinton and Salakhutdinov contributed to efficient data compression and dimensionality reduction, enabling faster processing of large medical datasets. Neuro-symbolic AI approaches proposed by d'Avila Garcez et al. combined deep learning with symbolic reasoning to enhance interpretability and decision-making capabilities, although integration complexity remains a challenge.

Furthermore, emerging paradigms such as spiking neural networks (SNNs) and spiking GANs have introduced energy-efficient and temporally aware learning mechanisms into DFU analysis. Studies by Roy et al. demonstrated that SNNs can effectively model temporal dynamics associated with ulcer progression while reducing energy consumption, making them suitable for real-time healthcare applications. Similarly, spiking GANs explored by Kim et al. combined generative modeling with biologically inspired neural processing to improve efficiency and temporal feature representation. Despite these promising advancements, several challenges persist across the literature. High computational complexity, data heterogeneity, lack of standardized datasets, and limited interpretability continue to hinder widespread clinical adoption. Additionally, integrating multiple advanced techniques into a unified, scalable framework remains a complex task. Nevertheless, the collective findings of these studies highlight that the integration of hybrid models, multimodal data, advanced optimization strategies, and scalable deployment solutions provides a strong foundation for developing accurate, efficient, and clinically applicable DFU diagnostic systems.

Comparative Table

Study	Year	Method	Model	Data Type	Key Contribution	Performance
1	2020	CNN	ResNet	Image	DFU classification	High accuracy
2	2021	GAN	DCGAN	Image	Data augmentation	Improved generalization
3	2020	Segmentation	U-Net	Image	Ulcer boundary detection	High Dice score
4	2021	Hybrid DL	CNN + Features	Image	Improved interpretability	Robust accuracy
5	2022	Attention DL	CNN + Attention	Image	Region focus	Reduced false positives
6	2021	GAN	Dual Discriminator GAN	Image	Improved segmentation	Stable training
7	2022	SNN	Spiking NN	Image/Temporal	Energy efficiency	Competitive results
8	2020	Transfer Learning	VGG/ResNet	Image	Small dataset learning	High accuracy
9	2021	Multimodal DL	CNN + Clinical	Image + Clinical	Improved prediction	Enhanced accuracy
10	2022	Optimization	Metaheuristic	Mixed	Parameter tuning	Faster convergence
11	2021	Transformer	ViT	Image	Global feature capture	High performance
12	2020	Ensemble	Multiple DL	Image	Robust predictions	Improved accuracy
13	2022	Edge AI	Lightweight CNN	Image	Real-time detection	Low latency
14	2021	XAI	Explainable DL	Image	Interpretability	Improved trust
15	2022	Reinforcement Learning	DRL	Mixed	Adaptive optimization	Efficient tuning
16	2020	Capsule Net	CapsNet	Image	Spatial hierarchy	Improved robustness
17	2021	Self-Supervised	SSL Model	Image	Reduced labeling	Strong generalization
18	2020	Federated	FL Model	Distributed	Privacy	Comparable

		Learning			preservation	accuracy
19	2020	Lightweight CNN	MobileNet	Image	Mobile deployment	Efficient inference
20	2021	Hybrid GAN	GAN + CNN	Image	Feature enhancement	Improved accuracy
21	2022	Multi-task	Shared Model	Image	Joint learning	Efficient performance
22	2021	Graph NN	GNN	Structured	Relationship modeling	Better prediction
23	2020	Contrastive Learning	SimCLR	Image	Feature extraction	Improved representation
24	2020	Autoencoder	Deep AE	Image	Compression	Efficient storage
25	2022	Transformer	Swin Transformer	Image	Segmentation	High accuracy
26	2021	Neuro-Symbolic	Hybrid AI	Mixed	Reasoning + Learning	Improved interpretability
27	2020	Bayesian DL	Probabilistic NN	Image	Uncertainty estimation	Reliable predictions
28	2021	Few-shot	Meta-learning	Image	Low data learning	Moderate accuracy
29	2022	Edge-Cloud	Hybrid System	Image	Scalability	Reduced latency
30	2022	Spiking GAN	SNN + GAN	Image	Energy-efficient GAN	Promising results

Analysis Based on Literature Review

The reviewed literature demonstrates a clear evolution from traditional convolutional neural networks toward more advanced and hybrid deep learning architectures for diabetic foot ulcer analysis. Early approaches primarily focused on classification using CNNs and transfer learning, achieving high accuracy but lacking generalization and interpretability. The introduction of generative adversarial networks significantly addressed data scarcity issues by enabling synthetic data generation, while dual-discriminator architectures further enhanced stability and segmentation performance. Recent advancements emphasize multimodal learning, integrating clinical and imaging data to improve predictive accuracy. Spiking neural networks and energy-efficient models have emerged as promising solutions for real-time and resource-constrained environments. Additionally, optimization techniques, including metaheuristics and reinforcement learning, have improved convergence and model adaptability. Transformer-based models and self-supervised learning approaches indicate a shift toward leveraging large-scale data and reducing annotation dependency. Overall, the trend highlights a movement toward hybrid, efficient, and interpretable systems capable of addressing complex clinical challenges.

Discussion

The integration of deep learning, generative models, and optimization techniques has significantly advanced the field of diabetic foot ulcer prediction and analysis. Dual-discriminator GANs have improved segmentation accuracy and training stability, while spiking neural networks introduce energy-efficient computation and temporal modeling capabilities. Multimodal approaches enhance predictive performance by incorporating diverse data sources, enabling more comprehensive clinical insights. Despite these advancements, several challenges remain, including data heterogeneity, limited availability of annotated datasets, and high computational requirements. Model interpretability continues to be a critical factor for clinical adoption, necessitating the integration of explainable AI techniques. Furthermore, real-world deployment requires robust, scalable, and efficient systems capable of operating in diverse healthcare environments. The combination of optimization strategies with advanced architectures offers promising solutions, but further research is needed to standardize methodologies and improve reproducibility.

Conclusion

This review highlights the significant progress in applying deep learning and optimization techniques for the classification and segmentation of diabetic foot ulcers. The emergence of dual-discriminator spiking generative adversarial networks represents a novel and promising direction, combining the strengths of adversarial learning and biologically inspired computation. These models demonstrate improved accuracy, efficiency, and adaptability, making them suitable for real-time clinical applications. However, challenges such as data scarcity, computational complexity, and lack of interpretability must be addressed to ensure widespread adoption. Future research should focus on developing lightweight, explainable, and multimodal systems that integrate clinical expertise with advanced AI techniques. Additionally, the exploration of federated learning and edge computing can facilitate secure and scalable deployment in healthcare settings. Overall, the convergence of deep learning, optimization, and innovative architectures holds great potential for improving diabetic foot ulcer management and patient outcomes.

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