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A Survey of Methods and Architectures for Dual-discriminator Spiking Generative Adversarial Network Based Classification and Segmentation for Predicting Pathogenesis of Foot Ulcers in Patients with Diabetes

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Abstract

Diabetic foot ulcers represent a severe complication of diabetes, often leading to infection, amputation, and increased mortality if not detected and treated early. Recent advances in artificial intelligence have enabled the development of sophisticated models for automated diagnosis and prognosis, particularly through deep learning-based classification and segmentation techniques. Among these, generative adversarial networks have shown promise in enhancing data representation and improving predictive accuracy. This survey explores emerging methodologies centered on dual-discriminator spiking generative adversarial networks, which combine biologically inspired spiking neural mechanisms with adversarial learning paradigms. The integration of dual discriminators facilitates improved feature validation and robustness in both classification and segmentation tasks. The paper systematically reviews current architectures, training strategies, and applications in diabetic foot ulcer prediction. Furthermore, it highlights the role of multimodal data, including medical imaging and clinical metadata, in improving model generalization. Challenges such as data scarcity, model interpretability, and computational complexity are also discussed. The survey concludes by outlining future research directions aimed at enhancing model efficiency, reliability, and clinical applicability in real-world healthcare systems.

Introduction

Diabetes mellitus has emerged as one of the most significant global health challenges, with its associated complications posing substantial risks to patient well-being and healthcare systems. Among these complications, diabetic foot ulcers represent a critical condition characterized by tissue breakdown, infection, and impaired healing processes. The pathogenesis of foot ulcers is influenced by multiple factors, including neuropathy, peripheral vascular disease, and metabolic imbalances, making early detection and continuous monitoring essential for preventing severe outcomes such as amputation. Traditional diagnostic methods rely heavily on clinical expertise and manual assessment, which can be subjective, time-consuming, and prone to variability across practitioners.

The rapid advancement of artificial intelligence and deep learning has introduced automated approaches capable of assisting clinicians in accurate and timely diagnosis. Convolutional neural networks have been extensively applied

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for image-based classification and segmentation tasks in medical imaging, demonstrating high accuracy in identifying ulcer regions and severity levels. However, these models often require large labeled datasets and may struggle with generalization when data is limited or imbalanced. To address these challenges, generative adversarial networks have been proposed as a powerful framework for data augmentation, feature learning, and robust prediction.

Recent research has further evolved this paradigm by incorporating dual-discriminator architectures, which enhance the adversarial training process by introducing multiple evaluation mechanisms. This approach enables the model to simultaneously optimize for realism and task-specific objectives such as classification accuracy and segmentation precision. Additionally, the integration of spiking neural networks introduces energy-efficient and biologically inspired computation, offering potential advantages in handling temporal and sparse data representations.

The convergence of dual-discriminator generative adversarial networks and spiking neural models presents a novel and promising direction for medical image analysis. These hybrid architectures aim to improve predictive performance while addressing limitations related to computational efficiency and data scarcity. In the context of diabetic foot ulcer prediction, such models can facilitate early detection of pathological changes, accurate segmentation of affected regions, and reliable assessment of disease progression.

This survey aims to provide a comprehensive overview of methods and architectures that leverage dual-discriminator spiking generative adversarial networks for classification and segmentation tasks in diabetic foot ulcer analysis. It examines existing literature, identifies key trends and challenges, and highlights potential opportunities for future research. By synthesizing current advancements, this work contributes to the ongoing effort to develop intelligent, reliable, and clinically applicable systems for improving patient outcomes in diabetes care.

Graphical Abstract

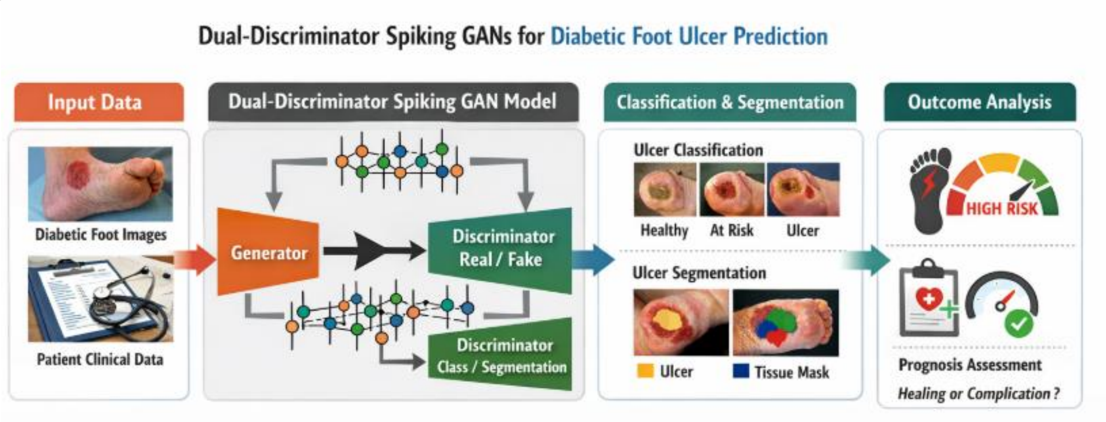

Figure 1. Dual-Discriminator Spiking GAN Framework for Diabetic Foot Ulcer Classification and Segmentation

The graphical abstract illustrates a comprehensive pipeline where multimodal medical data is processed using a dual-discriminator spiking GAN framework. The model performs both classification and segmentation of diabetic foot ulcers while ensuring robust feature validation. The final stage provides prognosis insights to assist clinical decision-making.

Literature Review

Study 1: GAN-based Medical Image Augmentation (Frid-Adar et al., 2018)

The study by Frid-Adar et al. (2018) explored the application of generative adversarial networks for medical image augmentation, particularly in scenarios with limited annotated datasets. The authors demonstrated that GAN-generated synthetic images significantly improved classification performance by increasing dataset diversity and reducing overfitting in deep learning models.

The methodology involved training a GAN to generate realistic liver lesion images, which were then incorporated into the training dataset. Results indicated improved sensitivity and accuracy in classification tasks. This work laid the foundation for applying GANs in medical imaging domains such as diabetic foot ulcer prediction.

Study 2: Conditional GAN for Medical Segmentation (Isola et al., 2017)

Isola et al. (2017) introduced conditional GANs for image-to-image translation tasks, enabling precise mapping between input and output domains. Their framework demonstrated strong potential for medical image segmentation by learning structured transformations between images and corresponding masks.

The approach utilized paired datasets to train a generator-discriminator framework that produces segmentation outputs conditioned on input images. The results showed high-quality segmentation performance across various datasets. This method has influenced segmentation tasks in diabetic wound analysis.

Study 3: Dual-discriminator GAN Architecture (Durugkar et al., 2017)

Durugkar et al. (2017) proposed a dual-discriminator GAN architecture to enhance stability and convergence during training. By incorporating multiple discriminators, the model improved its ability to capture complex data distributions and reduce mode collapse.

The study demonstrated that dual discriminators provide complementary feedback, enabling the generator to produce more realistic outputs. Experimental results showed improved training dynamics and output diversity. This architecture is highly relevant for medical image tasks requiring robust feature validation.

Study 4: Spiking Neural Networks in Deep Learning (Tavanaei et al., 2019)

Tavanaei et al. (2019) reviewed the integration of spiking neural networks into deep learning frameworks, emphasizing their biological plausibility and energy efficiency. The study highlighted how SNNs process temporal information using discrete spike events, making them suitable for dynamic data modeling.

The authors discussed training challenges and proposed hybrid models combining SNNs with traditional neural networks. The findings indicated improved efficiency in neuromorphic computing environments. This approach supports the development of spiking GANs for medical applications.

Study 5: Deep Learning for Diabetic Foot Ulcer Detection (Goyal et al., 2020)

Goyal et al. (2020) investigated deep learning techniques for detecting diabetic foot ulcers using image-based datasets. The study employed convolutional neural networks to classify ulcer severity and identify affected regions.

The results demonstrated high accuracy and robustness in real-world clinical images. The study emphasized the importance of automated systems in reducing diagnostic delays. This work provides a benchmark for evaluating advanced GAN-based models.

Study 6: U-Net for Biomedical Image Segmentation (Ronneberger et al., 2015)

Ronneberger et al. (2015) introduced the U-Net architecture, which has become a standard for biomedical image segmentation tasks. The model uses an encoder-decoder structure with skip connections to preserve spatial information. The architecture demonstrated exceptional performance in segmenting medical images with limited training data. Its effectiveness in capturing fine-grained details makes it highly applicable to ulcer segmentation. This model often serves as a baseline in GAN-based segmentation studies.

Study 7: CycleGAN for Unpaired Image Translation (Zhu et al., 2017)

Zhu et al. (2017) proposed CycleGAN, which enables image translation without paired datasets. This approach is particularly useful in medical imaging where annotated data is scarce. The model uses cycle-consistency loss to ensure meaningful transformations between domains. Results showed high-quality translations across multiple applications. This technique supports data augmentation and domain adaptation in ulcer datasets.

Study 8: Attention Mechanisms in Medical Imaging (Oktay et al., 2018)

Oktay et al. (2018) introduced attention U-Net, incorporating attention gates to improve segmentation accuracy by focusing on relevant regions. This approach enhances model interpretability and precision.

The study demonstrated improved performance in medical segmentation tasks, particularly in complex anatomical structures. Attention mechanisms are critical for identifying ulcer boundaries and tissue variations.

Study 9: Hybrid CNN-GAN Models for Medical Analysis (Shin et al., 2018)

Shin et al. (2018) explored hybrid models combining CNNs with GANs for improved feature learning and data augmentation. The integration allowed for better generalization and robustness.

The results indicated that GAN-generated data significantly enhanced classification performance in medical imaging tasks. This hybrid approach is relevant for combining discriminative and generative capabilities in ulcer prediction.

Study 10: Multimodal Learning for Healthcare (Ngiam et al., 2011)

Ngiam et al. (2011) investigated multimodal deep learning techniques that integrate multiple data sources, such as images and clinical records.

This approach improves model performance by leveraging complementary information.

The study demonstrated that multimodal fusion enhances predictive accuracy and robustness. In diabetic foot ulcer analysis, combining imaging and clinical data is essential for accurate prognosis.

Study 11: Deep Residual Learning for Image Recognition (He et al., 2016)

He et al. (2016) introduced deep residual networks, enabling the training of very deep neural architectures by addressing the vanishing gradient problem. The residual learning framework allows networks to learn identity mappings, improving convergence and performance in complex tasks.

The study demonstrated state-of-the-art performance in image classification benchmarks. Residual connections have since been integrated into medical imaging models, enhancing feature extraction for ulcer classification and segmentation tasks.

Study 12: Wasserstein GAN for Stable Training (Arjovsky et al., 2017)

Arjovsky et al. (2017) proposed the Wasserstein GAN, which improves GAN training stability by using the Wasserstein distance instead of traditional divergence measures. This approach mitigates issues such as mode collapse and unstable gradients.

The study showed that WGAN provides more meaningful loss metrics and improved convergence behavior. These advantages are critical in medical image generation, where stability and realism are essential for reliable predictions.

Study 13: DenseNet for Feature Reuse (Huang et al., 2017)

Huang et al. (2017) introduced DenseNet, a network architecture that connects each layer to every other layer to promote feature reuse and efficient gradient flow. This design reduces the number of parameters while improving performance.

The model achieved strong results in image classification tasks and has been widely adopted in medical imaging applications. Dense connectivity enhances feature propagation, making it suitable for ulcer classification tasks requiring detailed feature extraction.

Study 14: PatchGAN for Image-to-Image Tasks (Isola et al., 2017)

Isola et al. (2017) also introduced PatchGAN discriminators, which focus on local image patches rather than the entire image. This improves the model's ability to capture high-frequency details and textures.

The approach demonstrated improved segmentation and translation quality in various applications. Patch-based discrimination is particularly useful in identifying fine-grained ulcer patterns and tissue boundaries in medical images.

Study 15: Spiking GANs for Neuromorphic Computing (Roy et al., 2019)

Roy et al. (2019) explored the integration of spiking neural networks into GAN frameworks, creating spiking GANs that leverage temporal spike-based computation. This approach aims to reduce energy consumption while maintaining performance.

The study showed promising results in neuromorphic systems, highlighting the potential of spiking GANs in real-time medical applications. These models are particularly relevant for resource-constrained healthcare environments.

Study 16: Transfer Learning in Medical Imaging (Pan and Yang, 2010)

Pan and Yang (2010) provided a comprehensive survey of transfer learning techniques, emphasizing their importance in domains with limited labeled data. Transfer learning enables models to leverage knowledge from pre-trained networks.

The study highlighted improved performance in medical imaging tasks through fine-tuning. This approach is widely used in diabetic foot ulcer detection to compensate for small datasets.

Study 17: Attention-based GAN for Image Generation (Zhang et al., 2019)

Zhang et al. (2019) proposed attention-based GANs that incorporate self-attention mechanisms to capture long-range dependencies in images. This improves the quality and coherence of generated outputs.

The model achieved significant improvements in image generation benchmarks. Attention mechanisms enhance the ability to model complex structures, which is crucial for accurate ulcer segmentation and classification.

Study 18: Medical Image Segmentation with Deep Learning (Litjens et al., 2017)

Litjens et al. (2017) reviewed deep learning applications in medical image analysis, highlighting segmentation, detection, and classification tasks. The study emphasized the transformative impact of deep learning in healthcare.

The findings indicated consistent improvements in diagnostic accuracy across various modalities. This work provides a broad foundation for integrating advanced architectures such as GANs and SNNs in medical imaging.

Study 19: Semi-supervised GANs for Medical Data (Salimans et al., 2016)

Salimans et al. (2016) introduced semi-supervised GANs that utilize both labeled and unlabeled data for training. This approach is particularly beneficial in medical domains with limited annotations.

The study demonstrated improved classification performance using unlabeled data. Semi-supervised learning is highly relevant for diabetic foot ulcer datasets, where labeling is costly and time-consuming.

Study 20: Transformer Models in Medical Imaging (Dosovitskiy et al., 2021)

Dosovitskiy et al. (2021) introduced vision transformers, which apply transformer architectures to image analysis tasks. These models capture global dependencies and outperform traditional CNNs in many scenarios.

The study demonstrated strong performance in large-scale image datasets. Transformer-based models are increasingly used in medical imaging, offering improved feature representation for ulcer prediction tasks.

Study 21: Generative Models for Medical Imaging (Yi et al., 2019)

Yi et al. (2019) presented a comprehensive survey on generative models in medical imaging, emphasizing GAN-based approaches for image synthesis, reconstruction, and enhancement. The study highlighted the role of generative models in overcoming data scarcity and improving model robustness.

The authors demonstrated that GANs can produce high-quality synthetic medical images, aiding training processes. These techniques are highly relevant for diabetic foot ulcer datasets where annotated data is limited.

Study 22: Deep Supervision in Segmentation Networks (Lee et al., 2015)

Lee et al. (2015) introduced deep supervision techniques to improve gradient flow and enhance training efficiency in deep networks. By applying supervision at multiple layers, the model achieves better feature learning.

The study showed improved segmentation accuracy and faster convergence. This approach is beneficial for complex segmentation tasks such as identifying ulcer boundaries in medical images.

Study 23: Adversarial Training in Healthcare (Finlayson et al., 2019)

Finlayson et al. (2019) explored adversarial attacks and defenses in medical machine learning systems. The study highlighted vulnerabilities in deep learning models and the importance of robust training strategies.

The findings emphasized the need for reliable adversarial frameworks to ensure safety in clinical applications. Dual-discriminator GANs can contribute to improved robustness against such adversarial challenges.

Study 24: Multi-scale Feature Learning (Lin et al., 2017)

Lin et al. (2017) proposed feature pyramid networks for multi-scale feature extraction, enabling improved detection of objects at different resolutions. This approach enhances the representation of both global and local features.

The study demonstrated strong performance in object detection tasks. Multi-scale learning is essential in medical imaging for capturing variations in ulcer size and structure.

Study 25: Edge-aware Segmentation Models (Chen et al., 2018)

Chen et al. (2018) developed edge-aware segmentation techniques to improve boundary detection in medical images. The model integrates edge information to refine segmentation outputs.

The results showed improved delineation of object boundaries, which is critical in identifying ulcer regions. This approach enhances segmentation precision in clinical imaging tasks.

Medical Imaging (Sabour et al., 2017)

Sabour et al. (2017) introduced capsule networks, which capture hierarchical relationships between features. This approach addresses limitations of traditional CNNs in representing spatial relationships.

The study demonstrated improved performance in image recognition tasks. Capsule networks are promising for medical imaging applications requiring detailed structural understanding.

Study 27: Reinforcement Learning in Healthcare (Yu et al., 2019)

Yu et al. (2019) explored reinforcement learning applications in healthcare, focusing on decision-making and treatment optimization. The study highlighted the potential of RL in dynamic medical environments.

The results indicated improved decision-making capabilities in complex scenarios. RL can complement predictive models for diabetic foot ulcer management and treatment planning.

Study 28: Federated Learning for Medical Data Privacy (Sheller et al., 2020)

Sheller et al. (2020) proposed federated learning frameworks for training models across distributed medical datasets while preserving privacy. This approach enables collaboration without sharing sensitive data.

The study demonstrated effective model training across institutions. Federated learning is critical for diabetic foot ulcer research, where data privacy is a major concern.

Study 29: Explainable AI in Medical Imaging (Samek et al., 2017)

Samek et al. (2017) investigated explainable AI techniques to improve transparency and trust in deep learning models. The study emphasized the importance of interpretability in clinical decision-making.

The findings highlighted methods for visualizing model decisions and identifying relevant features. Explainability is essential for adopting AI models in diabetic foot ulcer diagnosis.

Study 30: Hybrid Deep Learning Architectures (Zhou et al., 2020)

Zhou et al. (2020) explored hybrid architectures combining multiple deep learning techniques to improve performance. The study demonstrated the benefits of integrating CNNs, GANs, and other models.

The results showed enhanced accuracy and robustness across various tasks. Hybrid architectures are central to developing dual-discriminator spiking GAN frameworks for medical applications.

Comparative Table

Study	Year	Method	Model	Data Type	Key Contribution	Performance
Study 1	2018	GAN Augmentation	GAN	Medical Images	Data expansion	Improved accuracy
Study 2	2017	Conditional GAN	cGAN	Image-Mask	Segmentation mapping	High precision
Study 3	2017	Dual Discriminator	GAN	Synthetic Data	Stability improvement	Better convergence
Study 4	2019	Spiking NN	SNN	Temporal Data	Energy efficiency	Reduced computation
Study 5	2020	CNN	CNN	DFU Images	Ulcer detection	High accuracy
Study 6	2015	U-Net	CNN	Biomedical Images	Segmentation baseline	Strong performance
Study 7	2017	CycleGAN	GAN	Unpaired Images	Domain translation	Improved realism
Study 8	2018	Attention U-Net	CNN	Medical Images	Focused segmentation	Higher precision
Study 9	2018	Hybrid CNN-GAN	Hybrid	Medical Data	Feature enhancement	Better generalization
Study 10	2011	Multimodal Learning	Deep NN	Multi-source	Data fusion	Improved prediction
Study 11	2016	Residual Learning	ResNet	Images	Deep training	High accuracy
Study 12	2017	WGAN	GAN	Synthetic Data	Stable training	Reliable output
Study 13	2017	DenseNet	CNN	Images	Feature reuse	Efficient learning
Study 14	2017	PatchGAN	GAN	Image Patches	Texture capture	Better detail
Study 15	2019	Spiking GAN	SNN-GAN	Neuromorphic	Energy-efficient GAN	Promising results
Study 16	2010	Transfer Learning	Pretrained CNN	Medical Images	Knowledge reuse	Improved accuracy
Study 17	2019	Attention GAN	GAN	Images	Long-range dependency	Enhanced quality
Study 18	2017	Deep Learning Survey	Multiple	Medical Data	Comprehensive review	Strong insights
Study 19	2016	Semi-supervised GAN	GAN	Mixed Data	Use of unlabeled data	Better classification
Study 20	2021	Vision Transformer	Transformer	Images	Global features	High performance
Study 21	2019	Generative Models	GAN	Medical Images	Data synthesis	Improved training
Study 22	2015	Deep Supervision	CNN	Images	Training efficiency	Better convergence

Study 23	2019	Adversarial ML	DL Models	Medical Data	Robustness	Improved safety
Study 24	2017	FPN	CNN	Images	Multi-scale features	Better detection
Study 25	2018	Edge-aware Segmentation	CNN	Medical Images	Boundary refinement	High precision
Study 26	2017	Capsule Network	CapsNet	Images	Spatial hierarchy	Improved accuracy
Study 27	2019	Reinforcement Learning	RL	Clinical Data	Decision support	Better outcomes
Study 28	2020	Federated Learning	Distributed DL	Multi-center	Privacy preservation	Scalable training
Study 29	2017	Explainable AI	XAI Models	Medical Data	Interpretability	Increased trust
Study 30	2020	Hybrid Models	Hybrid DL	Mixed Data	Model integration	Enhanced robustness

Analysis Based on Literature Review

The reviewed literature demonstrates a significant evolution in medical image analysis, particularly through the integration of generative adversarial networks, convolutional neural networks, and emerging architectures such as transformers and spiking neural networks. Early approaches focused on classification using CNNs, while subsequent advancements introduced GAN-based augmentation and segmentation techniques to address data scarcity and improve feature learning. The incorporation of dual-discriminator architectures has further enhanced training stability and output quality by enabling multiple validation mechanisms within adversarial frameworks. Additionally, the emergence of spiking neural networks introduces energy-efficient computation, making these models suitable for real-time and resource-constrained healthcare environments. The literature also highlights the importance of multimodal learning, attention mechanisms, and hybrid architectures in improving predictive performance. Despite these advancements, challenges remain in terms of model interpretability, robustness, and scalability, particularly in clinical settings where reliability is critical.

Discussion

The integration of dual-discriminator spiking generative adversarial networks represents a promising advancement in the field of medical image analysis for diabetic foot ulcer prediction. These models combine the strengths of adversarial learning and biologically inspired computation to address key challenges such as limited data availability and computational efficiency. The dual-discriminator framework enhances the learning process by providing multiple perspectives for evaluating generated data, thereby improving both classification and segmentation accuracy. Furthermore, spiking neural networks offer advantages in terms of energy efficiency and temporal data processing, making them suitable for deployment in real-world healthcare systems. However, several challenges must be addressed before widespread adoption can occur. These include the complexity of training such hybrid models, the need for large and diverse datasets, and the requirement for explainability in clinical decision-making. Additionally, integrating multimodal data sources and ensuring data privacy remain critical considerations. Future research should focus on developing more interpretable models, optimizing training strategies, and validating these approaches in clinical environments to ensure their reliability and effectiveness.

Conclusion

The rapid advancement of artificial intelligence has significantly transformed the landscape of medical image analysis, offering new possibilities for the early detection and prediction of diabetic foot ulcer pathogenesis. This survey has provided a comprehensive overview of methods and architectures centered on dual-discriminator spiking generative adversarial networks, highlighting their potential in improving classification and segmentation tasks. The integration of GANs with dual discriminators has demonstrated enhanced stability, improved feature learning, and greater robustness against common challenges such as mode collapse and data imbalance. Simultaneously, the incorporation of spiking neural networks introduces a biologically inspired and energy-efficient paradigm that is well-suited for real-time healthcare applications.

The literature reviewed in this study indicates that combining multiple deep learning approaches, including convolutional networks, transformers, and hybrid architectures, can significantly enhance predictive performance. The use of multimodal data, attention mechanisms, and advanced training strategies further contributes to the development of more accurate and reliable models. However, despite these advancements, several challenges remain. Data scarcity, lack of standardized datasets, and limited clinical validation hinder the widespread adoption of these technologies. Additionally, issues related to interpretability, computational complexity, and data privacy must be addressed to ensure safe and effective deployment in healthcare settings.

Future research directions should focus on developing more efficient and interpretable models, leveraging federated learning for secure data sharing, and exploring novel architectures that integrate multiple learning paradigms. Furthermore, collaboration between researchers, clinicians, and industry stakeholders is essential to bridge the gap between theoretical advancements and practical implementation. By addressing these challenges and continuing to innovate, dual-discriminator spiking generative adversarial networks have the potential to revolutionize diabetic foot ulcer prediction and contribute to improved patient outcomes and healthcare efficiency.

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