Biomedical Signal Processing and Control 113 (2026) 109127

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Towards accurate diabetic retinal disease detection using advanced deep metric learning

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ARTICLE INFO

Keywords:
Diabetic retinal disease
Contrast-Limited Adaptive Histogram Equalization
Bilateral filtering
Canny edge detection
EfficientNet
Bregman divergence

ABSTRACT

Retinal diseases remain a primary cause of irreversible vision loss worldwide, making early and precise diagnosis of conditions like diabetic retinopathy, glaucoma, and age-related macular degeneration critically important. However, effective retinal image analysis is challenged by factors such as noise, low contrast, and complex anatomical structures, especially when detecting fine vessel boundaries and subtle pathological lesions. To address these limitations, this research proposes a novel Retinal Efficient Deep Metric Learning Framework (RetinaEX-Net) that combines edge-aware image enhancement, high-dimensional embedding, and adaptive classification for robust disease detection. The framework introduces a Smart Adaptive Retinal Pre-processing (SARP) method, which integrates CLAHE (Contrast Limited Adaptive Histogram Equalization) and bilateral filtering, followed by Canny edge detection to enhance structural detail while minimizing artifacts. Feature embeddings are extracted using EfficientNet, with clustering performed using k-Means based on Empirical Bregman Divergence, and classification achieved through a confidence-aware k-NN approach. This architecture enables precise discrimination even in early-stage or ambiguous cases. Experimental evaluations on RFMiD and APTOS 2019 datasets show that RetinaEX-Net achieves up to 98.86% accuracy and a Cohen's Kappa score of 98.24%, outperforming state-of-the-art models. RetinaEX-Net offers a scalable, interpretable, and clinically deployable artificial intelligence (AI) solution, where AI specifically refers to the integration of deep metric learning, efficient convolutional feature extraction (EfficientNet), adaptive clustering using Bregman divergence, and confidence-aware k-NN classification. This makes the system well-suited for real-time screening in tele ophthalmology and resource-constrained healthcare environments.

1. Introduction

Vision plays a vital role in human perception, directly influencing quality of life, mobility, and overall well-being. Among the various threats to visual health, retinal diseases remain some of the most severe, often progressing silently before noticeable symptoms appear [1]. Age-related glaucoma, diabetic retinopathy, and macular degeneration are among the leading causes of vision loss and blindness worldwide. With the global prevalence of diabetes and aging populations steadily rising, the number of individuals at risk for retinal diseases is expected to increase significantly in the coming years [2]. Early detection of retinal diseases is crucial, as intervention can effectively slow or halt disease progression, thereby preserving vision and preventing irreversible damage. In most cases, retinal disorders exhibit subtle pathological changes in their early stages, which can be identified through routine screening using fundus photography or optical coherence tomography (OCT) [3]. However, manual analysis of retinal images requires a lot of time, requires trained specialists, and is subject to inter-observer variability, which can compromise diagnostic consistency and delay treatment. Retinal images contain a wealth of diagnostic information, capturing the intricate vascular structures, the optic disc, macula, and pathological lesions such as hemorrhages, exudates, or microaneurysms [4]. Nonetheless, interpreting these images presents several technical challenges. Factors such as poor lighting, variable contrast, and noise artifacts can obscure critical features and hinder accurate diagnosis. Furthermore, retinal images acquired from different populations and under varied conditions often exhibit substantial heterogeneity in appearance, requiring robust preprocessing and analytical techniques to ensure reliable evaluation [5]. Another challenge lies in the complex structure of the retina itself. Lesions and anomalies associated with

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https://doi.org/10.1016/j.bspc.2025.109127
Received 30 July 2025; Received in revised form 7 October 2025; Accepted 2 November 2025
Available online 15 November 2025

diabetic retinopathy and other retinal disorders are often small and visually similar to normal anatomical features, making them difficult to detect with basic image analysis [6]. Accurate recognition and classification demand sophisticated algorithms capable of discerning nuanced differences in shape, texture, and intensity across different regions of the image [7]. Fig. 1 shows the Fundus image of a Diabetic Retina annotated with its anatomical landmarks, including the optic disc, macula, and primary blood vessel networks. This visualization provides essential context for understanding the structural regions analyzed in automated diabetic retinal disease detection systems.

The complexity increases in the presence of co-existing conditions, further emphasizing the need for intelligent diagnostic support systems. In recent years, the incorporation of artificial intelligence (AI) into the field of medical imaging has opened new possibilities for retinal disease detection. AI-driven systems have demonstrated the ability to process large volumes of data efficiently, learning from patterns that may be imperceptible to the human eye [15]. This has paved the way for the development of computer-aided diagnostic tools that not only assist ophthalmologists but also enable scalable screening solutions, which are particularly beneficial in resource-limited settings [16]. The deployment of such systems has the potential to bridge the gap between increasing demand for retinal screening and limited availability of specialized healthcare professionals [17]. Thus, achieving reliable detection and classification of retinal diseases necessitates an integrated and intelligent diagnostic framework. Such a system must be capable of enhancing image quality, highlighting clinically significant features, and offering robust classification across diverse datasets [18]. The consequence of this work lies in its potential to develop early-stage retinal disease detection, reduce diagnostic delays, and extend quality eye care to underserved populations. By focusing on these areas, an AI-driven solution can help bridge the gap between the increasing demand for retinal screening and limitations of existing diagnostic practices, contributing meaningfully to the global effort to prevent avoidable blindness [19]. Despite progress in retinal imaging and diagnostics, accurate and early detection of diabetic retinal diseases continues to face significant challenges [20]. Fundus images are often marred by noise, low contrast, and lighting inconsistencies, which obscure important diagnostic details [21]. Additionally, current diagnostic approaches largely depend on manual interpretation by specialists, introducing variability in consistency and limiting accessibility in remote or resource-limited settings [22]. Many existing automated systems lack the precision needed to detect subtle pathological variations, leading to inconsistent classification results [23]. Therefore, there is a critical need for a robust, AI-driven framework that can enhance image quality, extract meaningful features, and classify retinal diseases with high reliability and clinical relevance.

2. Main contributions

This study proposes a robust, AI-driven diagnostic framework designed to address the major limitations in current retinal disease detection methodologies. The primary contributions of this work include.

- A novel image preprocessing pipeline is proposed to enhance retinal image quality by reducing noise, improving contrast, and normalizing illumination variations, thereby preserving diagnostically significant features.
- An advanced feature extraction strategy is implemented, capable of identifying subtle pathological variations that are often missed by traditional techniques.
- A reliable classification model is developed to accurately differentiate between normal and diseased retinal conditions across heterogeneous datasets, improving generalizability and clinical applicability.
- The proposed framework offers scalability and adaptability, making it suitable for deployment in limited and remote healthcare settings, thus contributing to broader accessibility to early retinal disease screening.

By integrating pre-processing, structural enhancement, and intelligent classification into a unified solution, Retinal Efficient Deep Metric Learning sets a new standard in automated retinal disease diagnosis.

The structure of this document is organized as follows: Section 1 outlines the background of the study, detailing the research objectives and underlying motivation. Section 2 provides a review of existing literature and identifies the research gap. Section 3 describes the proposed methodology in detail. Section 4 presents the results, interprets the findings, and offers a comparative analysis with existing methods. Section 5 concludes the study and discusses potential directions for future research. The References section includes all cited works that support the content of this study.

3. Literature Survey

Recent years have witnessed significant advances in automated retinal disease detection, with researchers exploring diverse strategies ranging from fuzzy clustering to multi-modal deep learning frameworks as shown in Table 1.

Early attempts focused on unsupervised learning approaches to reduce reliance on annotated data. For example, Luo et al. [8] introduced a Self-Supervised Fuzzy Clustering Network (SFCN), which combined feature learning, reconstruction, and fuzzy self-supervision. This approach effectively handled diverse datasets but faced challenges in generalizing to complex or subtle pathological variations.

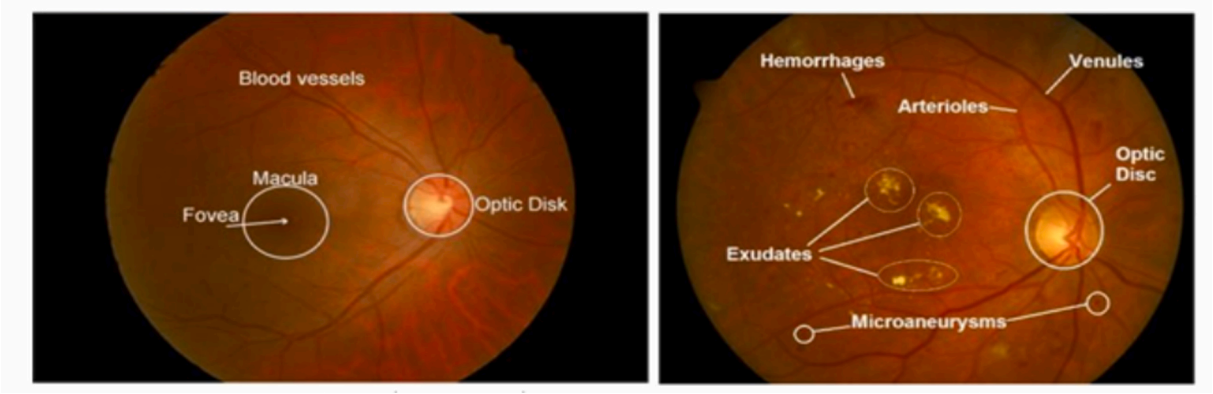

Fig. 1. Fundus Diabetic Retinal with anatomic structure.

with AUC values consistently above 0.97 and reaching 1.00 in several folds. On the APTOS-2019 dataset, the model demonstrated even stronger performance, achieving 98.9 % accuracy with precision, recall, and F1-score all at 98.8 %, and a kappa score of 98.2 %. In comparative evaluations, the proposed framework consistently outperformed or remained highly competitive with a broad range of state-of-the-art methods. On RFMiD, RetinaEX-Net delivered comparable performance to strong baselines such as UniFormer-B, BiFormer-B, TransMIL, MViTv2, ViT-CoMer, EfficientViT, MIL-ViT, and AMSFuse, while maintaining high robustness and generalizability. On APTOS-2019, the proposed model significantly surpassed all existing techniques, including AMSFuse and other transformer-based models, establishing clear superiority in both accuracy and reliability. These results collectively affirm the effectiveness, scalability, and clinical potential of RetinaEX-Net for automated retinal disease classification. The justification for this work lies in its ability to address critical limitations of previous methods, such as inadequate edge preservation, noise amplification, and over-simplified clustering, by integrating advanced pre-processing, efficient feature extraction, and adaptive classification techniques into a unified system. For future work, the model could be enhanced by incorporating attention mechanisms or transformers for even more refined feature extraction. Additionally, real-time deployment in clinical settings and expansion to multi-modal imaging data could further elevate the practical impact of this research in facilitating early diagnosis and personalized treatment planning of retinal diseases.

Ethical approval

Institutional Review Board approval was not required.

8. Consent for participate

All contributors agreed and given consent to participate.

9. Consent for Publication

All contributors agreed and given consent to Publish.

Author contribution

The authors confirm contribution to the paper as follows and all authors reviewed the results and approved the final version of the manuscript.

Funding

The authors state that this work has not received any funding.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data will be shared upon request.

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