International Journal of Recent Research and Review, Vol. XVIII, Issue 1, March 2025
ISSN 2277 – 8322

DEVELOPMENT OF A DEEP LEARNING-BASED COMPUTER-AIDED DIAGNOSTIC SYSTEM FOR DETECTION AND SEVERITY ANALYSIS OF DIABETIC RETINOPATHY USING RETINAL FUNDUS IMAGES

Aakash Nama
M.Tech Scholar
Department of Computer Science and Engineering
Rajasthan Institute of Engineering & Technology, Jaipur

Ms. Pragya Bharti
Assistant Professor
Department of Computer Science and Engineering
Rajasthan Institute of Engineering & Technology, Jaipur

Abstract: Diabetic Retinopathy (DR) is a progressive eye disease and a leading cause of vision impairment and blindness among diabetic individuals worldwide. Early diagnosis and timely intervention are essential to prevent permanent vision loss. This research presents the development of a computer-aided diagnostic (CAD) system that leverages deep learning for the automatic detection and severity analysis of diabetic retinopathy using retinal fundus images.The proposed system focuses on three primary components: retinal blood vessel segmentation, detection of cotton wool spots (white lesions indicating disease severity), and classification of retinal images into normal and abnormal categories. The methodology integrates spatially adaptive contrast enhancement with a modified Tyler Coye algorithm and Hough line transformation to improve blood vessel visibility and reconstruction. This hybrid vessel segmentation technique significantly enhances the detection of fine vascular structures and pathological features.A deep Convolutional Neural Network (CNN) model is designed and trained on publicly available STARE and DRIVE datasets. Preprocessing techniques such as normalization, data augmentation, and contrast adjustment are employed to improve the robustness and accuracy of the model. Experimental results indicate that the system achieves 82% classification accuracy on the STARE dataset and 91.5% on the DRIVE dataset with preprocessing, outperforming standard deep learning approaches like ResNet under the same conditions.This study demonstrates the

effectiveness of the proposed deep learning-based CAD system in replicating ophthalmological evaluations for DR screening. The system's scalability and high performance make it particularly valuable for early-stage diagnosis and grading of diabetic retinopathy in clinical and resource-constrained environments. Overall, the research contributes a reliable and automated solution to assist healthcare professionals in managing diabetic eye care, thereby reducing the global burden of vision loss due to diabetic retinopathy.
Keywords: Diabetic Retinopathy, Retinal Fundus Images, Deep Learning, Convolutional Neural Network, STARE Database, DRIVE Database, Vessel Segmentation, Cotton Wool Spots, Preprocessing, Image Classification, Computer-Aided Diagnosis, Medical Image Analysis, Retinal Abnormalities, Severity Grading, Ophthalmology.

Introduction

Diabetic Retinopathy (DR) is a serious microvascular complication of diabetes mellitus and is widely recognized as one of the foremost causes of vision impairment and blindness across the globe. It occurs due to prolonged hyperglycemia that damages the blood vessels in the retina, leading to leakage, blockage, or abnormal vessel growth, which in turn can severely impair vision or even result in total blindness if not detected and treated in time. With the rising global prevalence of diabetes, especially in low- and middle-income countries, the burden of diabetic retinopathy is expected to increase significantly in the coming years. According to the International Diabetes Federation, over 500 million people worldwide are currently living with diabetes, and it is estimated that more than one-third of these individuals may develop some form of DR during their lifetime. Early-stage DR is typically asymptomatic, which poses a major challenge for diagnosis and timely medical intervention. Therefore, effective screening, early detection, and accurate grading of DR are of critical importance for initiating timely treatment and preventing irreversible vision loss. Traditional screening methods such as ophthalmoscopy and fluorescein angiography, though effective, are resource-intensive, subjective, and require skilled professionals, which may not always be feasible in rural or under-resourced regions. In this context, the development of a Computer-Aided Diagnostic (CAD) system offers a promising solution for scalable, cost-effective, and rapid screening of diabetic retinopathy. Recent advances in artificial intelligence, particularly in the domain of deep learning, have revolutionized the field of medical image analysis by enabling automatic detection of disease patterns with high accuracy and minimal human intervention. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in image classification, object detection, and semantic segmentation, making them ideal candidates for the development of intelligent diagnostic tools. This research aims to leverage the capabilities of deep learning techniques to design and implement a CAD system that can automatically detect and grade the severity of diabetic retinopathy using retinal fundus images. The proposed system focuses on three major components: segmentation of retinal blood vessels, detection and analysis of cotton wool spots (CWS)—a key indicator of disease severity—and classification of fundus images into normal and abnormal categories. Blood vessel segmentation is a vital step in retinal image analysis as it helps in identifying vascular abnormalities, which are primary indicators of the disease. However, the task is challenging due to the presence of noise, low contrast, and varying illumination in fundus images. To address these challenges, this study introduces a hybrid vessel segmentation approach that combines spatially adaptive contrast enhancement with a modified Tyler Coye algorithm, further improved by Hough line transformation for effective vessel reconstruction. This novel combination significantly enhances the visibility and continuity of fine vessels and supports accurate pathological feature extraction. For the detection of cotton wool spots, image processing techniques are utilized to identify white fluffy lesions, which are indicative of retinal ischemia and are crucial in grading the severity of DR. Furthermore, for classification purposes, a deep CNN architecture is designed and trained using publicly available datasets—STARE and DRIVE—which are widely used benchmarks for retinal image analysis. Preprocessing steps such as contrast adjustment, normalization, and data augmentation are incorporated to improve the quality and diversity of training data, thereby enhancing the generalization capability and robustness of the model. The CNN model is optimized and validated across multiple experimental settings, and the results demonstrate that the proposed system achieves a classification accuracy of 82% on the STARE dataset and 91.5% on the DRIVE dataset with preprocessing, which significantly outperforms traditional models and baseline CNNs without preprocessing. Additionally, a comparative analysis with state-of-the-art deep learning methods such as ResNet shows that the proposed system is not only more accurate but also computationally efficient and easier to deploy in real-world settings. This indicates the practical applicability of the system in clinical environments and also in remote or resource-limited areas where expert ophthalmologists may not be readily available. The motivation behind this research lies in the urgent need for automated and reliable screening tools that can assist healthcare providers in early detection and timely treatment planning of diabetic retinopathy. The proposed CAD system not only aims to improve the accuracy of diagnosis but also reduces the burden on medical professionals by providing a second opinion that mimics the decision-making process of an experienced ophthalmologist. Moreover, by utilizing open-access datasets and computationally efficient algorithms, the research ensures that the developed system can be adopted and scaled up with minimal cost. The contributions of this research are multifold: first, it introduces a robust vessel segmentation technique that addresses common challenges in fundus image analysis; second, it incorporates a lesion detection module focusing on cotton wool spots to support accurate grading of DR; third, it presents an end-to-end deep CNN-based classification model that demonstrates superior performance in experimental evaluations. The system's performance is validated using well-established datasets, ensuring the reliability and reproducibility of results. The significance of this work extends beyond academic interest; it holds immense potential for public health applications, especially in developing countries with high diabetic populations and limited access to ophthalmological care. In conclusion, this research represents a meaningful step toward the integration of deep learning and computer vision in medical diagnostics.

Figure1.Fundus ImageHavingRedLesions

By focusing on diabetic retinopathy—a leading yet preventable cause of blindness—the study addresses a critical healthcare challenge and offers a practical, intelligent, and scalable solution. The findings underscore the transformative role of artificial intelligence in healthcare and open new avenues for future research, including multi-disease detection systems, mobile-based diagnostic platforms, and integration with electronic health records for holistic patient care. As the world moves toward more personalized and technology-driven healthcare, such innovations will play a pivotal role in bridging the gap between demand and availability of quality medical services, ultimately contributing to better health outcomes and improved quality of life for diabetic patients worldwide.

Related Works

Diabetic Retinopathy (DR) detection through computer-aided systems has evolved considerably with the integration of deep learning and convolutional neural networks (CNNs). One innovative approach proposed by Borys Tymchenko et al. (2020) focuses on a self-learning strategy that analyzes DR progression from a single fundus image. Their multi-stage transfer learning strategy across similarly labeled datasets achieved a high specificity and sensitivity score of 0.99 and was competitively ranked 54 out of 2943 entries at APTOS 2019 with a quadratic kappa score of 0.925. In a complementary effort, P. Junjun et al. (2018) introduced a region selection mechanism (RSM) integrated with deep CNNs, which effectively highlights regions of interest (ROIs) based on discriminative features learned from large-scale datasets. Their study trained on 30,000 fundus images, and validated on 5,000 images, demonstrated reliable DR classification and localization of pathological features.

Augmentation and regularization techniques have also seen considerable refinement. A. Buslaev et al. (2018) developed "Albumentations," an efficient image augmentation library offering a wide range of transformation tools for enhancing training diversity and model robustness. In another work, Devries and Taylor (2017) proposed a simple yet powerful regularization method called “Cutout,” which masks random square regions of input images during training, resulting in improved generalization in CNNs. Similarly, Hu et al. (2017) introduced the "Squeeze-and-Excitation" (SE) block that adaptively recalibrates channel-wise feature responses, leading to improved CNN performance with minimal computational overhead, a strategy widely adopted in the later SENet architectures.

Transfer learning has also emerged as a practical solution for tackling limited labeled data in DR datasets. Hagos and Kant (2019) leveraged pre-trained Inception-V3 modules on a reduced Kaggle DR dataset, addressing data scarcity and achieving commendable classification performance. Carson Lam et al. (2018) validated their CNN model on DR staging using fundus images and achieved a validation sensitivity of 95%. They further observed that mild DR cases were often misclassified due to subtle features, which were better captured by employing adaptive histogram equalization and expert-verified labels. Transfer learning via pre-trained GoogleNet and AlexNet models further improved performance in staging tasks.

A wide spectrum of activation functions has been explored to improve the discriminative capability of CNNs. B. Xu et al. (2015) compared standard ReLU with variants like Leaky ReLU, PReLU, and RReLU and found that activation functions allowing a small non-zero gradient for negative inputs performed better, challenging traditional assumptions about sparsity in ReLU-based architectures. In a similar effort to optimize architectural scalability, Tan and Le (2019) proposed EfficientNets, which balance network depth, width, and resolution using a compound scaling method. EfficientNet-B7 achieved state-of-the-art performance on ImageNet while being significantly smaller and faster than conventional CNNs, demonstrating potential for portable DR diagnostic systems.

Several works have explored DR detection through novel segmentation and classification strategies. Iglovikov and Shvets (2018) used pre-trained encoders like VGG11 to improve U-Net-based architectures for precise image segmentation. L. Seoud et al. (2014) developed a multi-step approach for identifying microaneurysms and hemorrhages in fundus images using dynamic feature extraction and classification through Random Forest, with promising results across different camera sources. L. Shen et al. (2016) emphasized information-theoretic relay backpropagation in deep networks to enhance gradient flow during training, resulting in improved performance in scene classification challenges, while H. Pratt et al. (2016) applied CNNs trained on the Kaggle DR dataset for automatic classification of DR features like microaneurysms and exudates, reaching 75% classification accuracy with 95% sensitivity on 5,000 validation images.

Global Average Pooling (GAP) and interpretability have also been addressed by researchers like B. Zhou et al. (2016), who showed that CNNs trained for classification can inherently localize discriminative regions using GAP layers, facilitating object localization without explicit supervision. Z. Wang and J. Yang (2017) expanded on this by introducing RAM (Region Attention Maps), a visual interpretability tool that highlights areas contributing to DR predictions, helping clinicians understand model decisions. Similarly, H. Noh et al. (2017) introduced DELF (Deep Local Features), a CNN-based method suitable for large-scale image retrieval and DR detection, designed to capture semantically meaningful local features from fundus images.

Benchmarking and dataset development have also been critical in advancing DR research. Russakovsky et al. (2015) discussed the evolution of the ImageNet Large Scale Visual

Recognition Challenge (ILSVRC), which has significantly influenced CNN development and transfer learning practices in medical imaging. Szegedy et al. (2015, 2016) contributed significantly through the inception of GoogleNet and its improvements, achieving reduced top-5 error rates with efficient use of computing resources. Their designs emphasized balanced trade-offs between network depth and parameter efficiency. M. Sankar et al. (2016) provided a focused CNN approach to detect DR-related pathologies such as microaneurysms and exudates, aiding in classification of non-proliferative and proliferative DR stages.

Finally, Asiri et al. (2018) reviewed both traditional machine learning and deep learning methods in DR detection, highlighting the shift from handcrafted features to automated feature learning using deep networks. Their work emphasizes the importance of robust CAD systems for early diagnosis and discusses future challenges such as model generalization, interpretability, and data imbalance. Collectively, these studies provide a strong foundation for developing automated DR diagnostic tools using CNNs, transfer learning, image segmentation, and attention mechanisms, all of which contribute to improved early detection, grading, and management of diabetic retinopathy in clinical and remote settings.

ProposedMethodology

The methodology employed in this study integrates multiple steps focused on accurate localization of the fovea and the segmentation of blood vessels in digital fundus images, which are critical for the automatic detection and severity analysis of diabetic retinopathy. The initial stage involves the **localization of the fovea**, a key anatomical landmark situated approximately 2 optic disk diameters (2DD) temporal to the optic disc. Since the fovea lies within the macular region, accurate determination of its coordinates is essential for evaluating retinal health. In digital fundus images, vasculature appears as a network of vessels of varying thickness and length. This vasculature typically branches out from the optic disc in a tree-like pattern. The methodology leverages this network, identifying branches with the highest number of connected vessels. This data is then used to infer the optic disc region, where vessel branching is densest. The region that shows maximum vessel convergence is selected to represent the optic circle.

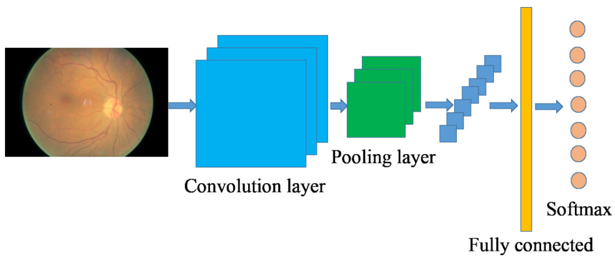

Figure2. Architecture of the Convolutional

Neural Network

Following this, the methodology employs a schematic representation of datasets like STARE and DRIVE to illustrate optic disc localization and vessel segmentation. In determining the vascular arcade, the approach utilizes the vascular tree and the position of the optic circle. A significant feature considered here is the “raphe”—a horizontal line passing through the center of the optic disc and fovea that divides the retina into superior and inferior regions. The detection of the raphe and the vascular arcade enables accurate measurement of the macular region. For this, an allegorical structure model is created using the distribution of the vasculature and the segmented vessel map vt(x,y)vt(x, y)vt(x,y). This structural representation helps define the optic surface plate, allowing the transformation of coordinates using axis rotation in two dimensions. The central location of the fovea is geometrically determined to be 2DD from the optic disc center along the principal axis of a fitted parabola. The foveal area, or macula candidate region, is defined as a circular region with a radius equal to 1DD.

The methodology then divides the fundus image into 10 anatomical subfields using three concentric circles centered at the fovea with radii of 13\frac{1}{3}31DD, 1DD, and 2DD. These subfields include a focal subfield within the innermost circle, four inner subfields between the inner and middle circles (sub-superior, inferior, temporal, and nasal), and four outer subfields between the middle and outer circles (outer superior, inferior, temporal, and nasal). This detailed mapping enables precise anatomical localization and disease analysis within specific retinal regions.

The second major part of the methodology involves **blood vessel segmentation**, which is vital for identifying diabetic retinopathy-associated abnormalities. Retinal vasculature analysis provides key insights into systemic conditions such as arteriosclerosis, hypertension, and diabetes. In fundus images, changes in the vascular network may indicate the presence of retinal pathologies. Vessel segmentation also facilitates retinal image registration, enabling follow-up examinations and targeted treatments. However, vessel segmentation is challenging due to low contrast regions, overlapping anatomical structures, and the presence of lesions.

To address these challenges, the study applies **histogram matching** using intensity data from the red and green channels of the fundus images. The red channel enhances the visual contrast of fundus images, particularly in areas with poor illumination. The histogram of the green channel is modified based on the red channel to generate a visually enhanced image that improves vessel visibility. A matched filter is applied to further enhance the contrast between the vasculature and background. The filter highlights linear structures by responding strongly to elongated, vessel-like patterns.

To segment vessels from the enhanced images, a **local relative entropy-based thresholding technique** is used. This method considers the spatial distribution of grayscale intensity levels, making it robust in cases where foreground and background regions overlap. It ensures preservation of fine vessel structures and minimizes false detections.

Following vessel segmentation, the process moves to **optic disc (OD) detection**, another vital component of the retinal anatomy. The OD is typically a bright circular region in the nasal part of the retina through which the central retinal artery and vein pass. Detecting the OD accurately is essential for localizing other anatomical structures like the macula and fovea. OD detection is achieved using the **Differential Windowing (DW) technique**, which combines edge detection with local maxima identification. The steps involved include mask generation to eliminate non-retinal background, pre-processing to enhance the optic disc, and morphological operations such as image opening and subtraction to isolate the optic cup.

In this method, average filtering is performed using a circular window of radius equal to 5% of the disc width, and the brightest region is selected as the optic cup. ROI (Region of Interest) is then defined using the disc's bounding circle, with the radius set to 1.5 times the disc width. To determine whether the image belongs to the left or right eye, vessel convergence within the ROI is analyzed. If vessel convergence occurs on the left, the image is classified as the left eye; otherwise, it is the right eye. This determination further guides the direction for theta angle calculation—counterclockwise for left eyes and clockwise for right.

To eliminate the impact of vessels on OD detection, morphological **dilation and erosion** operations are performed using a circular structuring element. This removes vascular artifacts from the OD and optic cup region, providing a clearer segmentation of these features. Once the optic disc is segmented, **Cartesian to Polar transformation** is applied for more effective analysis of circular structures. The transformation is centered on the optic cup, with a radius 1.5 times the disc width. The polar coordinates offer better visualization and feature extraction in radial and angular directions, improving segmentation accuracy.

The **final output** of this comprehensive methodology is a well-localized fovea and accurately segmented vessel network, which together form the foundation for diabetic retinopathy classification. These outputs are fed into a convolutional neural network (CNN) classifier for further analysis and grading. By employing these advanced image processing and geometric modeling techniques, the proposed method ensures high precision in identifying anatomical landmarks and pathological signs of diabetic retinopathy.

RESULTS

The evaluation of the proposed deep learning-driven computer-aided diagnostic system for detecting diabetic retinopathy, utilizing the STARE and DRIVE datasets, offers valuable insights into the role of preprocessing and the model's comparative efficiency over existing frameworks. This analysis underlines the critical contribution of preprocessing methods in enhancing the performance of convolutional neural networks (CNNs) for retinal fundus image analysis. An initial performance comparison was conducted on the STARE and DRIVE datasets, both with and without preprocessing. The results clearly demonstrate that preprocessing significantly improves classification accuracy—on the STARE dataset, accuracy rose from 74% without preprocessing to 82% with it, while the DRIVE dataset showed an improvement from 81% to 91.5%. These improvements are attributed to better contrast enhancement, more precise vessel segmentation, and more effective feature extraction, which collectively contribute to superior differentiation between healthy and pathological fundus images.

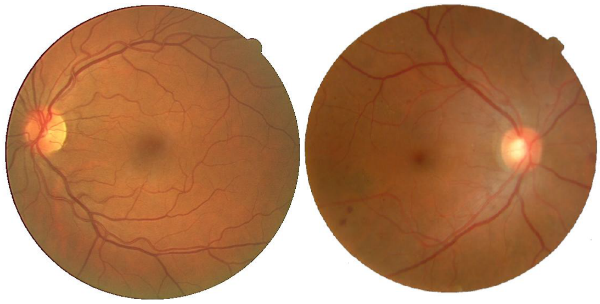

Figure 3 Schematic Sample of STARE and DRIVE Database

Figure 4. Segmentation of Blood Vessels

Further comparison was carried out against a previous deep learning model by Junjun et al. (2019), which implemented a ResNet-based architecture for DR detection. While the earlier model achieved accuracy in the range of 54% to 85%, the proposed CNN architecture delivered results ranging from 74% to 91.5%. One notable advantage of the proposed system is its use of two distinct datasets (STARE and DRIVE), offering better generalizability and reduced risk of overfitting, unlike the earlier single-dataset approach. Moreover, the CNN architecture was specifically tailored for retinal image analysis, making it more effective than general-purpose models like ResNet in capturing retinal features such as microaneurysms, vessel abnormalities, and cotton wool spots.

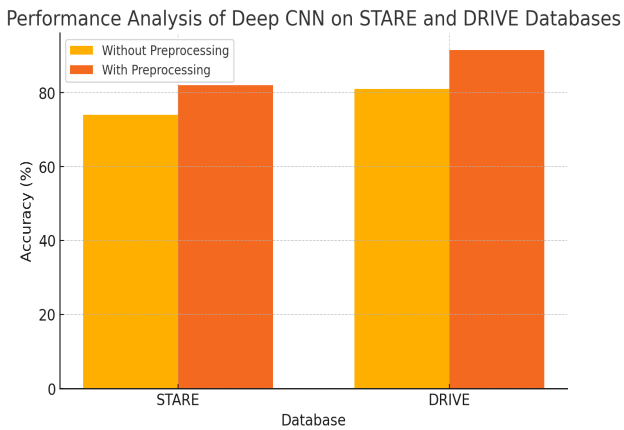

Figure 5 Performance Analysis of Proposed Methodology on Multiple Dataset

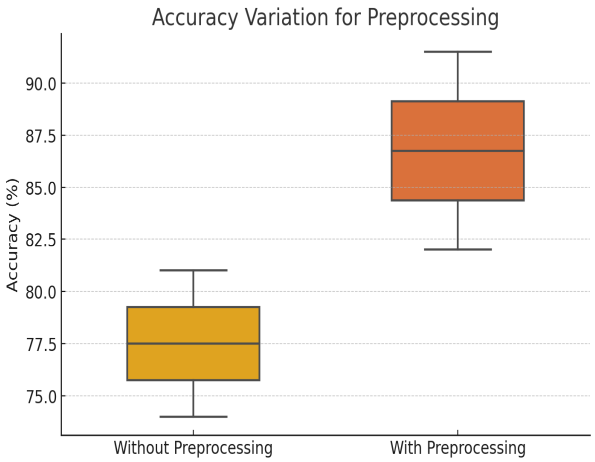

Figure 6 Accuracy Analysis of Pre-Processing

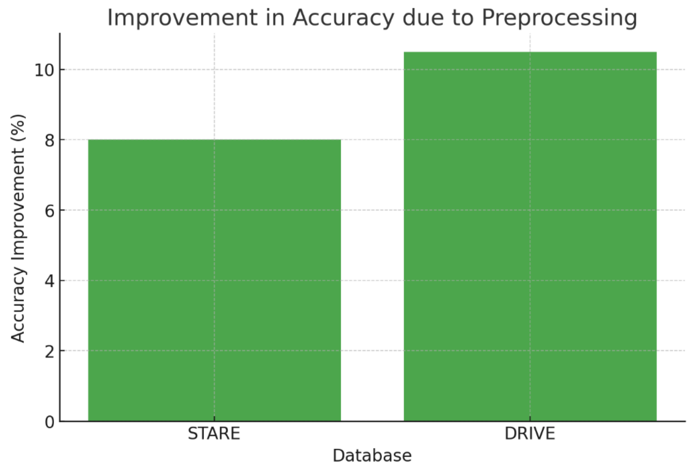

Figure 7 Analysis of Improvement in Accuracy

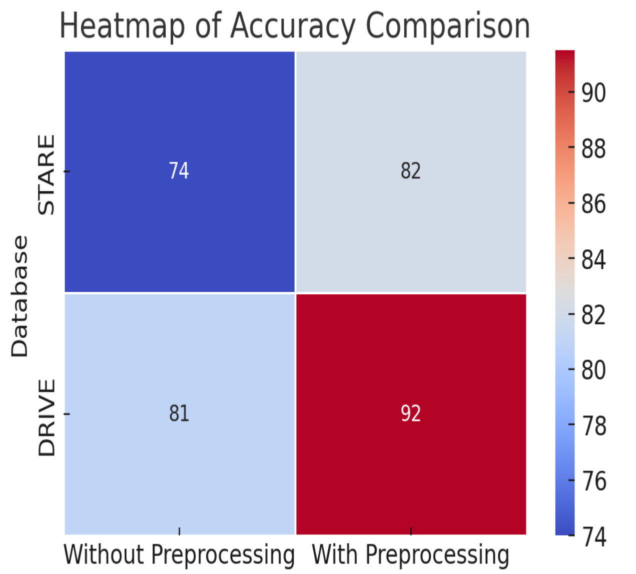

Figure 8 Analysis of Heatmap of Accuracy

To further validate the findings, a boxplot analysis was employed, illustrating the consistency and accuracy gains achieved through preprocessing. This representation revealed reduced variance and higher accuracy in model performance across multiple experimental runs. Notably, the DRIVE dataset experienced a 10.5% gain in accuracy post-preprocessing, compared to an 8% increase for the STARE dataset, indicating that preprocessing yields greater benefits for datasets with initially lower performance baselines. A supplementary heatmap visualization was also created to demonstrate accuracy variations across datasets and preprocessing conditions, further confirming the value of preprocessing in deep learning-based retinal analysis.

Overall, the study validates that integrating a structured preprocessing framework with a domain-optimized CNN architecture significantly improves diagnostic outcomes in diabetic retinopathy detection. Enhanced contrast, refined vessel segmentation, and accurate classification of pathological features underscore the effectiveness of the approach. Additionally, the adoption of a dual-database methodology emphasizes the importance of multi-source data in achieving robust and scalable computer-aided diagnostic systems. The research ultimately concludes that the proposed deep CNN model not only surpasses previous methods in accuracy and clinical applicability but also establishes a more generalizable solution for early detection and classification of diabetic retinopathy using retinal fundus images.

Conclusion

This research presents the development and performance evaluation of a deep learning-based computer-aided diagnostic system for the detection and severity analysis of diabetic retinopathy (DR) using retinal fundus images. By integrating advanced image preprocessing, vessel segmentation techniques, and a customized convolutional neural network (CNN) architecture, the system achieves high accuracy in identifying retinal abnormalities associated with DR. The study utilized two benchmark datasets—STARE and DRIVE—to validate the robustness and generalizability of the proposed model. Results demonstrated that preprocessing techniques significantly improve classification performance, with accuracy improving from 74% to 82% on STARE and from 81% to 91.5% on DRIVE. These enhancements highlight the importance of contrast adjustment, vessel segmentation, and noise removal in improving feature extraction and deep model training.

Furthermore, comparative analysis with an existing ResNet-based method confirmed that the proposed CNN model outperforms traditional architectures in both accuracy and consistency. The system's dual-database approach provides a more comprehensive evaluation, reducing the risks of overfitting and enhancing the generalization capability of the model. Boxplot and heatmap analyses further reinforced the findings, demonstrating the positive impact of preprocessing across various experimental setups and datasets.

In conclusion, the proposed system offers a reliable, scalable, and cost-effective solution for early-stage DR screening, particularly useful in resource-constrained settings. By automating the detection and severity grading of diabetic retinopathy, the model supports ophthalmologists in making timely clinical decisions and reducing the risk of vision loss in diabetic patients. This work lays the groundwork for future advancements in AI-based ophthalmic diagnostics and encourages further exploration into multi-disease detection frameworks, real-time mobile-based applications, and integration with electronic health records for comprehensive diabetic eye care.

REFERENCES

[1] Borys Tymchenko, Philip Marchenko and Dmitry Spodarets (2020). Deep Learning Approach to Diabetic Retinopathy Detection, ArXiv e-prints.

[2] P. Junjun, Y. Zhifan, S. Dong and Q. Hong (2018). Diabetic Retinopathy Detection Based on Deep Convolutional Neural Networks for Localization of Discriminative Regions," International Conference on Virtual Reality and Visualization (ICVRV), 2018, pp. 46-52, doi: 10.1109/ICVRV.2018.00016, IEEE.

[3] A. Buslaev, A. Parinov, E. K. V. I. I. and Kalinin, A. A. (2018). Albumentations: fast and flexible image augmentations. ArXiv e-prints.

[4] Asiri, N., Hussain, M., and Aboalsamh, H. A. (2018). Deep learning based computer-aided diagnosis systems for diabetic retinopathy: A survey. CoRR, abs/1811.01238.

[5] Carson Lam, Darvin Yi, M. G. and Lindsey, T. (2018). Automated detection of diabetic retinopathy using deep learning. AMIA Jt Summits Transl Sci Proc. 2018 May 18; 2017:147-155. PMID: 29888061; PMCID: PMC5961805.

[6] Devries, T. and Taylor, G. W. (2017). Improved regularization of convolutional neural networks with cutout. CoRR, abs/1708.04552.

[7] Hagos, M. T. and Kant, S. (2019). Transfer learning based detection of diabetic retinopathy from small dataset. CoRR, abs/1905.07203.

[8] Hu, J., Shen, L., and Sun, G. (2017). Squeeze-andexcitation networks. CoRR, abs/1709.01507.

[9] Iglovikov, V. and Shvets, A. (2018). Ternausnet: U-net with VGG11 encoder pre-trained on imagenet for image segmentation. CoRR, abs/1801.05746.

[10] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., and Wojna, Z. (2016). Rethinking the inception architecture for computer vision. In Proceedings of IEEE Conference on Computer Vision and Pattern Recognition.

[11] Tan, M. and Le, Q. V. (2019). Efficientnet: Rethinking model scaling for convolutional neural networks. cite arxiv:1905.11946Comment: Published in ICML 2019.

[12] B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba (2016). Learning deep features for discriminative localization. In Computer Vision and Pattern Recognition (CVPR), 2016 IEEE Conference on, pp. 2921– 2929. IEEE.

[13] Z. Wang and J. Yang (2017). Diabetic retinopathy detection via deep convolutional networks for discriminative localization and visual explanation. arXiv preprint arXiv:1703.10757.

[14] B. Xu, N. Wang, T. Chen, and M. Li (2015). Empirical evaluation of rectified activations in convolutional network. arXiv preprint arXiv:1505.00853.

[15] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A (2015). Rabinovich, et al. Going deeper with convolutions. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1-9, doi: 10.1109/CVPR.2015.7298594.

[16] L. Seoud, T. Faucon, T. Hurtut, J. Chelbi, F. Cheriet, and J. P. Langlois (2014). Automatic detection of microaneurysms and haemorrhages in fundus images using dynamic shape features. In Biomedical Imaging (ISBI), IEEE 11th International Symposium on, pp. 101–104. IEEE.

[17] L. Shen, Z. Lin, and Q. Huang (2016). Relay backpropagation for effective learning of deep convolutional neural networks. In European conference on computer vision, pp. 467–482. Springer.

[18] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein (2015). Imagenet large scale visual recognition challenge. International Journal of Computer Vision, 115(3):211–252.

[19] M. Sankar, K. Batri, and R. Parvathi (2016). Earliest diabetic retinopathy classification using deep convolution neural networks. pdf. Int. J. Adv. Eng. Technol, 2016.

[20] H. Noh, A. Araujo, J. Sim, T. Weyand, and B. Han (2017). Large-scale image

retrieval with attentive deep local features. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 3456–3465.

[21] H. Pratt, F. Coenen, D. M. Broadbent, S. P. Harding, and Y. Zheng (2016). Convolutional neural networks for diabetic retinopathy. Procedia Computer Science, 90:200–205.

[22] APTOS (2019). APTOS 2019 blindness detection. Accessed: 2019-10-20.

[23] EyePACs (2015). Diabetic retinopathy detection. Accessed: 2019-10-20.

[24] Google Brain (2018). Messidor-2 diabetic retinopathy grades. Accessed: 2019-10-20.

[25] Kaggle (2016): Diabetic rentinopathy detection challenge. http:// www.kaggle.com/c/diabetic-retinopathy-detection/data.