Review on Diabetic Retinopathy Detection through Deep Learning Techniques

Vishal Barot[1] Pratik Modi[2] Hitesh Barot[3] Piyush Kapadiya[4] Mehul P. Barot[5]
[1,2,3,4,5]LDRP Institute of Technology and Research, Kadi Sarva Vishwavidyalaya, Gujarat, India

Abstract— Diabetic retinopathy (DR) is a common complication of diabetes that can lead to vision loss if not detected and treated early. Deep learning techniques have shown great promise in the automated detection of DR from retinal images, offering a potential solution to the growing healthcare challenge. This survey paper provides an in-depth analysis of various deep learning methods and approaches used for diabetic retinopathy detection. We categorize the techniques into two main columns: Image-based and Non-image-based approaches, to offer a comprehensive understanding of the field.

Key words: Diabetic Retinopathy (DR), Deep Learning Techniques

I. INTRODUCTION

Diabetic retinopathy (DR) is a common and potentially vision-threatening complication of diabetes. It affects the retina and can lead to vision loss if not diagnosed and treated promptly. The condition progresses through various stages, including mild, moderate, severe non-proliferative DR (NPDR), and proliferative DR (PDR) [2]. Early detection and timely intervention are crucial for preventing vision impairment, making DR screening an essential part of diabetes management.

Deep learning techniques, a subset of artificial intelligence, have garnered considerable attention for their ability to automate DR detection from retinal images. This survey paper aims to provide a comprehensive overview of the various deep learning techniques and approaches employed in the diagnosis of diabetic retinopathy. We categorize these approaches into two main columns: Image-based and Non-image-based techniques, enabling readers to gain a thorough understanding of the current landscape of DR detection.

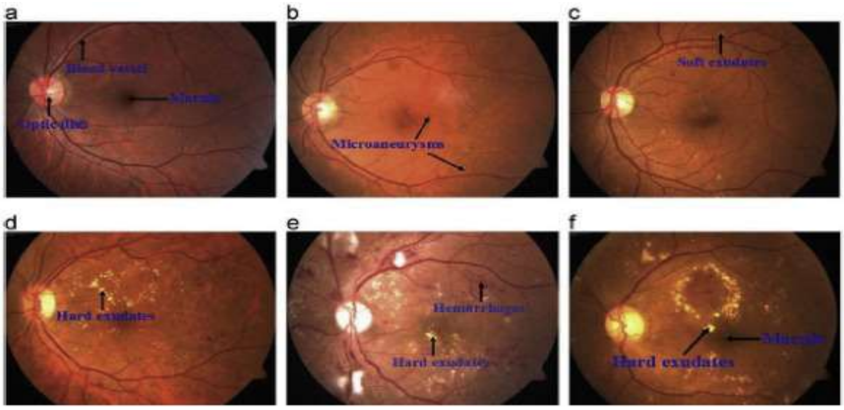

Fig. 1: The DR stages: (a) normal retinal (b) Mild DR, (c) Moderate DR, (d) Severe DR, (e) Proliferative DR,(f) Macular edema [1]

II. IMAGE-BASED APPROACHES

A. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) have revolutionized the field of computer vision and have proven to be highly effective in DR detection. These networks are specifically designed to handle image data, making them well-suited for the analysis of retinal images [3, 4, 5]. CNNs operate through convolutional layers that detect patterns, features, and textures within images, followed by pooling layers for spatial reduction and fully connected layers for decision making.

In the context of DR detection, various CNN architectures have been explored. These include LeNet, VGG, ResNet, and Inception, each with its unique strengths and applications. Researchers have found that pre-trained CNN models, which have been initially trained on vast image datasets, can be fine-tuned for DR detection[6], reducing the need for large annotated datasets and enhancing performance.

Furthermore, the preprocessing of retinal images plays a crucial role in enhancing the capabilities of CNNs. Techniques such as contrast enhancement, noise reduction, and data augmentation help in improving the quality of input images and robustness of the model [7, 8]. The application of CNNs to DR detection continues to evolve, with ongoing efforts to improve accuracy, speed, and scalability.

B. Segmentation-Based Approaches

Segmentation-based approaches focus on identifying and delineating specific retinal structures, such as blood vessels and lesions, as an integral step in DR detection. This enables the localization and quantification of abnormalities, which is essential for disease grading and monitoring.

Prominent segmentation architectures include U-Net and Fully Convolutional Networks (FCN). These networks are designed to produce pixel-wise segmentations, making them well-suited for identifying the extent and boundaries of retinal lesions[9]. However, creating high-quality pixel-level annotations for training can be challenging and time-consuming.

In practice, a combination of segmentation and classification is often employed. This involves first segmenting the relevant structures, and then utilizing the segmented regions for further analysis and classification. This fusion of segmentation and classification techniques can improve the overall accuracy of DR detection models, enabling finer-grained analysis and diagnosis.

C. Ensemble Techniques

Ensemble techniques offer a means to enhance the robustness and reliability of DR detection models. These methods combine multiple models or predictions to arrive at a more accurate and stable diagnosis.

Bagging and boosting are two widely used ensemble techniques. Bagging involves training multiple models on subsets of the dataset and aggregating their outputs, reducing the risk of overfitting. Boosting, on the other hand, iteratively adjusts the weights of training examples to give more emphasis to previously misclassified instances, thereby improving model performance.

Another approach to ensembling involves stacking multiple deep learning models, which combines their predictions at a higher level to make the final diagnosis. This approach has shown promise in achieving better generalization and improved performance.

Ensemble techniques have emerged as effective strategies for addressing common challenges in DR detection, such as class imbalance and model variability. These methods are valuable tools for increasing diagnostic accuracy and building more reliable systems for diabetic retinopathy screening.

III. NON-IMAGE-BASED APPROACHES

A. Feature Extraction and Selection

While deep learning models have shown exceptional performance in DR detection, non-image-based approaches, such as feature extraction and selection, continue to play a significant role. These methods involve manually defining and extracting relevant features from retinal images [10]. These features can be based on texture, color, shape, or other characteristics that may be indicative of diabetic retinopathy.

Dimensionality reduction techniques, such as Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE), are applied to reduce the dimensionality of feature vectors, making them more manageable and interpretable. Feature selection methods help identify the most relevant features and improve model efficiency.

Understanding the importance of specific features in diabetic retinopathy detection is crucial, as it provides insights into the underlying mechanisms of the disease. Non-image-based approaches complement image-based techniques and can be valuable in situations where deep learning models may not be feasible or where interpretability is of utmost importance [11, 12].

B. Multimodal Data Fusion

Incorporating information beyond retinal images is another avenue for enhancing the accuracy and reliability of DR detection models. Multimodal data fusion combines retinal images with additional clinical data, such as patient demographics, medical history, and lab results, to provide a more comprehensive view of a patient's health [13, 14].

Fusion strategies can be categorized into early fusion, where different data types are combined at the input level, and late fusion, where predictions from separate models are integrated at a later stage. Early fusion combines diverse data sources into a unified representation, while late fusion allows separate models to make individual predictions that are then combined.

This integration of multimodal data has shown the potential to improve diagnostic accuracy, especially when dealing with complex medical conditions like diabetic retinopathy [15]. By considering not only the retinal images but also the patient's overall health and history, the model gains a more holistic perspective, contributing to more informed decision-making.

C. Transfer Learning from Other Medical Domains

Transfer learning leverages knowledge from related medical domains to improve diabetic retinopathy detection. In scenarios where sufficient annotated data for diabetic retinopathy may be limited, transferring knowledge from other medical image analysis tasks offers an attractive solution.

Transfer learning involves adapting pre-trained models from related domains, such as general ophthalmology or other retinal conditions. This approach capitalizes on the shared features and patterns present in medical images, reducing the need for extensive data collection and annotation [16].

While transfer learning offers the potential to jumpstart model development, it also presents challenges, such as domain shift and model biases. Researchers are exploring techniques to mitigate these challenges and ensure the successful transfer of knowledge for improved diabetic retinopathy detection.

IV. EVALUATION METRICS AND DATASETS

A. Commonly used evaluation metrics

The evaluation of diabetic retinopathy detection models relies on various performance metrics, each providing valuable insights into a model's effectiveness. Sensitivity, specificity, area under the Receiver Operating Characteristic (ROC) curve (AUC), and F1-score are among the most commonly used metrics [17].

- Sensitivity (True Positive Rate) measures the proportion of true positives correctly identified by the model, indicating its ability to detect cases of diabetic retinopathy.
- Specificity (True Negative Rate) quantifies the model's accuracy in identifying non-diabetic retinopathy cases.
- AUC summarizes the model's overall performance in distinguishing between normal and diabetic retinopathy cases, with a higher AUC indicating better discrimination [19].
- F1-score balances the trade-off between precision and recall, providing a single measure of a model's performance.
- Selecting the appropriate evaluation metrics depends on the specific goals of the DR detection system, considering factors like the relative importance of false positives and false negatives.

Sr no	Accuracy	Method Name
1	98.60%	CNN-Transformer hybrid model [18]
2	95%	Multi-scale feature extraction CNN [20]
3	96.80%	CNN with contextual information [21]
4	98.60%	Transformer neural network [25]
5	99.10%	Combination of CNN and RNN [26]
6	98.20%	Ensemble learning [27]
7	97.50%	Data augmentation [29]
8	99.30%	Attention-based CNN [30]

Table 1: Accuracy of the different methods used

B. Popular Diabetic Retinopathy Datasets

Several datasets have been widely adopted in the development and benchmarking of diabetic retinopathy detection models. These datasets are essential for training and evaluating models, and they differ in terms of size, diversity, and the presence of annotations [22, 23].

The Kaggle Diabetic Retinopathy Detection dataset is one of the most well-known and frequently used datasets in the field. It contains a large collection of retinal images with associated annotations for disease severity grading. The IDRiD dataset (Indian Diabetic Retinopathy Image Dataset) comprises retinal images from diabetic patients and is notable for its variety in terms of image quality and diabetic retinopathy stages.

The Messidor dataset is another widely utilized dataset that includes retinal images and annotations for diabetic retinopathy grading[24].

The EyePACS dataset is a valuable resource that features a diverse range of retinal images, making it a suitable choice for training and validating models.

The choice of dataset depends on research objectives, data availability, and the need for domain-specific characteristics. These datasets play a pivotal role in advancing the development and evaluation of diabetic retinopathy detection algorithms.

V. CHALLENGES AND FUTURE DIRECTIONS

A. Challenges in DR detection

The field of diabetic retinopathy detection faces several challenges that necessitate ongoing research and innovation: Class imbalance: Imbalanced datasets, where certain classes (e.g., severe cases) are underrepresented, can lead to biased models. Addressing class imbalance is crucial for achieving reliable and equitable detection.

Generalization to diverse populations: Models trained on one demographic group may not generalize well to others. Ensuring that DR detection models are robust across diverse patient populations is essential for real-world applicability.

Explainability and trustworthiness of models: In medical applications, the interpretability of model decisions is critical. Ensuring that deep learning models are transparent and can provide explanations for their predictions is an ongoing challenge.

B. Future directions

The future of diabetic retinopathy detection holds promising directions:

- Explainable AI for medical applications: Developing methods for explaining the decisions of deep learning models in medical contexts is crucial for gaining the trust of healthcare professionals and patients.
- Integration with electronic health records (EHRs): Combining DR detection with electronic health records allows for a more holistic understanding of a patient's health, enabling personalized treatment plans and longitudinal monitoring.
- Personalized medicine and telemedicine applications: The advancement of DR detection technologies will pave the way for personalized treatment strategies and telemedicine solutions, allowing for remote monitoring and timely intervention.

- These future directions highlight the potential for deep learning techniques to revolutionize diabetic retinopathy management and pave the way for more accessible and effective healthcare solutions.

VI. CONCLUSION

In conclusion, this survey paper has provided a comprehensive overview of the diverse landscape of deep learning techniques for diabetic retinopathy detection. From image-based approaches, including convolutional neural networks, segmentation-based methods, and ensemble techniques, to non-image-based approaches involving feature extraction, multimodal data fusion, and transfer learning, the field of DR detection is rich with innovation and potential.

The utilization of various evaluation metrics and access to diverse datasets have advanced our understanding of the disease and enabled the development of robust detection models. However, the challenges of class imbalance, generalization to diverse populations, and model explainability persist and call for continued research efforts.

Looking forward, the integration of diabetic retinopathy detection with electronic health records, the development of explainable AI for medical applications, and the rise of personalized medicine and telemedicine applications promise to enhance the impact of deep learning in the field. The combination of technological advancements and a deepening understanding of the disease will drive progress in diabetic retinopathy management and ultimately improve patient outcomes.

REFERENCES

[1] Mookiah, M. R. K., Acharya, U. R., Chua, C. K., Lim, C. M., Ng, E. Y. K., & Laude, A. (2013). Computer-aided diagnosis of diabetic retinopathy: A review. Computers in biology and medicine, 43(12), 2136-2155.
[2] M. T. Al-Antary and Y. Arafa, "Multi-Scale Attention Network for Diabetic Retinopathy Classification," in IEEE Access, vol. 9, pp. 54190-54200, 2021, doi: 10.1109/ACCESS.2021.3070685.
[3] Alyoubi, Wejdan L., Wafaa M. Shalash, and Maysoon F. Abulkhair. "Diabetic retinopathy detection through deep learning techniques: A review." Informatics in Medicine Unlocked 20 (2020): 100377.
[4] M. Mateen, J. Wen, M. Hassan, N. Nasrullah, S. Sun and S. Hayat, "Automatic Detection of Diabetic Retinopathy: A Review on Datasets, Methods and Evaluation Metrics," in IEEE Access, vol. 8, pp. 48784-48811, 2020, doi: 10.1109/ACCESS.2020.2980055.
[5] Nadeem, M.W.; Goh, H.G.; Hussain, M.; Liew, S.-Y.; Andonovic, I.; Khan, M.A. Deep Learning for Diabetic Retinopathy Analysis: A Review, Research Challenges, and Future Directions. Sensors 2022, 22, 6780. https://doi.org/10.3390/s22186780
[6] Lam, Carson, et al. "Automated detection of diabetic retinopathy using deep learning." AMIA summits on translational science proceedings 2018 (2018): 147.
[7] Tsiknakis, Nikos, et al. "Deep learning for diabetic retinopathy detection and classification based on fundus images: A review." Computers in biology and medicine 135 (2021): 104599.
[8] Al-Antary, Mohammad T., and Yasmine Arafa. "Multi-scale attention network for diabetic retinopathy classification." IEEE Access 9 (2021): 54190-54200.
[9] Raman, Rajiv, et al. "Fundus photograph-based deep learning algorithms in detecting diabetic retinopathy." Eye 33.1 (2019): 97-109.
[10] Dai, Ling, et al. "A deep learning system for detecting diabetic retinopathy across the disease spectrum." Nature communications 12.1 (2021): 3242.
[11] Tymchenko, Borys, Philip Marchenko, and Dmitry Spodarets. "Deep learning approach to diabetic retinopathy detection." arXiv preprint arXiv:2003.02261 (2020).
[12] Shekar S, Satpute N, Gupta A. Review on diabetic retinopathy with deep learning methods. J Med Imaging (Bellingham). 2021 Nov;8(6):060901. doi: 10.1117/1.JMI.8.6.060901. Epub 2021 Nov 29. PMID: 34859116; PMCID: PMC8628856.
[13] Mane, D., Londhe, N., Patil, N., Patil, O., Vidhate, P. (2022). A Survey on Diabetic Retinopathy Detection Using Deep Learning. In: Nanda, P., Verma, V.K., Srivastava, S., Gupta, R.K., Mazumdar, A.P. (eds) Data Engineering for Smart Systems. Lecture Notes in Networks and Systems, vol 238. Springer, Singapore.
[14] Mushtaq, Gazala, and Farheen Siddiqui. "Detection of diabetic retinopathy using deep learning methodology." IOP conference series: materials science and engineering. Vol. 1070. No. 1. IOP Publishing, 2021.
[15] Bala, Ruchika, Arun Sharma, and Nidhi Goel. "A lightweight deep learning approach for diabetic retinopathy classification." International Conference on Artificial Intelligence and Speech Technology. Cham: Springer International Publishing, 2021.
[16] Sebti, R., Zroug, S., Kahloul, L., & Benharzallah, S. (2021, November). A deep learning approach for the diabetic retinopathy detection. In The Proceedings of the International Conference on Smart City Applications (pp. 459-469). Cham: Springer International Publishing.
[17] Gangwar, A. K., & Ravi, V. (2021). Diabetic retinopathy detection using transfer learning and deep learning. In Evolution in Computational Intelligence: Frontiers in Intelligent Computing: Theory and Applications (FICTA 2020), Volume 1 (pp. 679-689). Springer Singapore.
[18] Sharma, A., Shinde, S., Shaikh, I. I., Vyas, M., & Rani, S. (2021, February). Machine learning approach for detection of diabetic retinopathy with improved pre-processing. In 2021 International conference on computing, communication, and intelligent systems (ICCCIS) (pp. 517-522). IEEE.

[19] Khan, Z., Khan, F. G., Khan, A., Rehman, Z. U., Shah, S., Qummar, S., ... & Pack, S. (2021). Diabetic retinopathy detection using VGG-NIN a deep learning architecture. IEEE Access, 9, 61408-61416.
[20] Venkaiahppalaswamy, B., Reddy, P. P., & Batha, S. (2023). Hybrid deep learning approaches for the detection of diabetic retinopathy using optimized wavelet based model. Biomedical Signal Processing and Control, 79, 104146.
[21] Suganyadevi, S., Renukadevi, K., Balasamy, K., & Jeevitha, P. (2022, February). Diabetic Retinopathy Detection Using Deep Learning Methods. In 2022 First International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT) (pp. 1-6). IEEE.
[22] Yadav, M., Goel, R., & Rajeswari, D. (2021, June). A Deep Learning Based Diabetic Retinopathy Detection from Retinal Images. In 2021 International Conference on Intelligent Technologies (CONIT) (pp. 1-5). IEEE.
[23] Gupta, S., Thakur, S., & Gupta, A. (2022). Optimized hybrid machine learning approach for smartphone based diabetic retinopathy detection. Multimedia Tools and Applications, 81(10), 14475-14501.
[24] Boral, Y. S., & Thorat, S. S. (2021, April). Classification of diabetic retinopathy based on hybrid neural network. In 2021 5th International Conference on Computing Methodologies and Communication (ICCMC) (pp. 1354-1358). IEEE.
[25] Zhang, C., Lei, T., & Chen, P. (2022). Diabetic retinopathy grading by a source-free transfer learning approach. Biomedical Signal Processing and Control, 73, 103423.
[26] Vij, R., & Arora, S. (2023). A systematic review on diabetic retinopathy detection using deep learning techniques. Archives of Computational Methods in Engineering, 30(3), 2211-2256.
[27] Jagan Mohan, N., Murugan, R., & Goel, T. (2022). Deep learning for diabetic retinopathy detection: Challenges and opportunities. Next Generation Healthcare Informatics, 213-232.
[28] Adriman, R., Muchtar, K., & Maulina, N. (2021). Performance evaluation of binary classification of diabetic retinopathy through deep learning techniques using texture feature. Procedia Computer Science, 179, 88-94.
[29] Bhandari, S., Pathak, S., & Jain, S. A. (2023). A literature review of early-stage diabetic retinopathy detection using deep learning and evolutionary computing techniques. Archives of Computational Methods in Engineering, 30(2), 799-810.
[30] Majumder, S., & Kehtarnavaz, N. (2021). Multitasking deep learning model for detection of five stages of diabetic retinopathy. IEEE Access, 9, 123220-123230.
[31] Atwany, M. Z., Sahyoun, A. H., & Yaqub, M. (2022). Deep learning techniques for diabetic retinopathy classification: A survey. IEEE Access, 10, 28642-28655.