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MACHINE LEARNING APPROACHES FOR DETECTING AND CLASSIFYING DIABETIC RETINOPATHY – A SURVEY

[1]M. Rajeswari, [2]Krishnapriya KS, [3]M. Sowmiya, [4]Anusree K, [5]Nimitha Jose Edassery

[1,5]Computer Science and Engineering, Karunya Institute of Technology and Sciences, Coimbatore, India, [1]rajeswari@karunya.edu
[2]Department of Computer Science, Valdosta University, Valdosta, GA, USA.
[3]Department of Artificial Intelligence and Data Science, Sri Eshwar College of Engineering, Coimbatore
[4]Department of Computer Science and Engineering, Sahrdaya College of Engineering and Technology, Kerala, India

Abstract— Diabetic retinopathy (DR), a common complication of diabetes affecting the small blood vessels in the retina, is a primary reason for vision impairment. Timely identification is essential in averting sight loss; however, the manual examination of retinal fundus images is labor-intensive and susceptible to inaccuracies. Machine learning (ML) offers a promising solution, with various algorithms demonstrating high accuracy in DR detection and classification. This paper surveys 15 recent studies on ML-based techniques for DR analysis. We compare and contrast the performance of different algorithms, including convolutional neural networks (CNNs), deep learning models like Swin Transformers, hybrid approaches combining CNNs with other methods, and feature fusion techniques. The reviewed studies utilize publicly available datasets and evaluate their model's using metrics like accuracy, sensitivity, specificity, and F1 score. Our analysis reveals that CNNs, particularly ResNet50 architectures, achieve high performance in DR detection and classification. Deep learning models like Swin Transformers demonstrate even greater accuracy, while hybrid approaches and feature fusion techniques offer additional advantages in classification and computational efficiency. The results underscore the capacity of machine learning to automate diabetic retinopathy screening, offering the promise of enhanced accessibility and precision when contrasted with conventional approaches. Future research directions include exploring explainable AI techniques for improved model interpretability and developing robust models that can generalize well across diverse datasets.

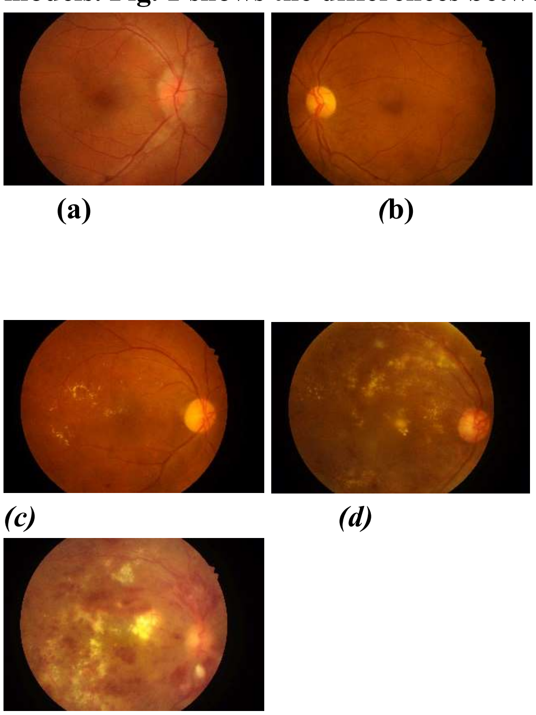
Keywords— Diabetic retinopathy, Machine learning techniques, Convolutional neural networks, Deep learning, Diabetic retinopathy detection, Diabetic retinopathy classification

1. Introduction

Diabetic retinopathy (DR) stands as a primary contributor to blindness in individuals with diabetes. This condition emerges from prolonged hyperglycemia, where elevated blood sugar levels harm the fragile blood vessels in the retina, the essential layer in the eye that processes light to enable vision. Over time, these damaged vessels can leak fluid, hemorrhage (bleed), or even completely block blood flow, leading to vision loss. Early identification and management of diabetic retinopathy (DR) play a crucial role in averting permanent vision loss. Nevertheless, the conventional approaches to DR screening involve the manual assessment of retinal fundus images by ophthalmologists, which can be laborious, subjective, and demanding in terms of resources.

This obstacle has prompted extensive exploration into utilizing artificial intelligence (AI) for the automated detection and categorization of diabetic retinopathy (DR). AI is a comprehensive concept covering various methods that empower machines to imitate human cognitive abilities like learning and problem-solving. Within this realm, machine learning (ML) stands as a subset of AI concentrated on algorithms capable of learning from data without direct programming. Specifically in the domain of diabetic retinopathy (DR), ML algorithms are trained on extensive sets of labeled retinal images, enabling them to recognize patterns and characteristics linked to both healthy and diseased retinas. These patterns, often invisible to the naked eye, can then be used to automatically classify new, unseen images.

Several publicly available datasets have been instrumental in advancing research on AI-based DR detection. The Messidor, E-Ophtha EX, IDRiD, and DIARETDB1 datasets are some prominent examples. These datasets consist of retinal images from patients with varying stages of DR, along with corresponding diagnoses from ophthalmologists. The quality and variety of these datasets are crucial for training robust and generalizable ML models. Fig. 1 shows the differences between retinas in different stages of DR.



(a) **(b)**

(c) ***(d)***

(e)

Fig. 1. Retina images (a) No DR (b) Mild DR (c) Moderate DR (d) Severe DR (e) Proliferative DR

The utilization of AI in the analysis of diabetic retinopathy (DR) presents numerous benefits. Initially, automation plays a pivotal role in diminishing the workload of ophthalmologists, enabling them to concentrate on intricate cases that demand their specialized knowledge. Second, AI algorithms can be trained to detect subtle features in retinal images that might be missed by human observers, leading to more accurate diagnoses. Third, AI-based systems can be deployed in resource-limited settings, where access to ophthalmologists might be limited, expanding access to DR screening for a wider population.

Despite these advantages, challenges remain. One key challenge is the imbalanced nature of DR datasets, where healthy images typically outnumber images with severe DR. This imbalance can bias the models towards healthy classifications and lead to underdiagnosis of DR. Another challenge is incorporating clinical expertise into AI models. While AI systems can excel at pattern recognition, they lack the contextual understanding and judgment of experienced ophthalmologists.

This survey paper delves into the current state-of-the-art AI approaches employed to detect and classify DR. By analyzing 15 recent research papers, various deep learning architectures, like convolutional neural networks, and their applications in automated DR analysis are explored. The strategies employed by researchers to overcome the limitations of imbalanced datasets and integrate clinical knowledge into AI models are examined. Finally, the future directions and potential impact of AI on improving DR screening and patient outcomes are discussed.

2. Machine learning techniques

The reviewed research leverages a diverse range of ML techniques for automated DR detection and classification. Here, some of the prominent methods encountered in the survey are explored.

2.1 Convolutional Neural Networks (CNNs)

- Inception V3, ResNet50, InceptionV3, EfficientNet B4, DenseNet201: These are pre-trained convolutional neural networks (CNNs) renowned for their exceptional performance across diverse image classification assignments. These networks are structured with convolutional layers that extract hierarchical features from retinal images, capturing detailed information from low-level to high-level semantics. The research studies frequently utilize transfer learning, a method where these pre-trained models are adjusted on diabetic retinopathy datasets to excel in distinguishing between healthy and diseased retinas.

- CNN + SVD (Singular Value Decomposition): This approach combines a CNN for feature extraction with Singular Value Decomposition (SVD) for dimensionality reduction. SVD helps to compress the extracted features while retaining essential information relevant for DR classification.

2.2 Deep Learning Architectures

- Faster RCNN + Feature Fusion: This method utilizes Faster RCNN, a deep learning architecture adept at object detection and localization. Here, it's used to identify specific regions of interest (ROIs) within the retinal image, potentially corresponding to DR lesions like microaneurysms or hemorrhages. Feature fusion techniques then combine these ROI-specific features with global image features extracted from a CNN for improved classification accuracy.

- **ADL-CNN (Active Deep Learning CNN):** This approach incorporates active learning strategies into a CNN architecture. Active learning allows the model to select the most informative data points for training, potentially leading to improved performance with less training data.

- CNN+MLELM (Extreme Learning Machine): This method combines a CNN for feature extraction with a modified Extreme Learning Machine for classification. MLELM is a learning algorithm known for its fast training speed, making it suitable for real-time applications.
- CNN with Intermediate Fusion: This technique leverages CNNs for feature extraction from different layers within the network architecture. These features are then fused at an intermediate level before feeding them into the final classification stage. This strategy seeks to encompass both intricate low-level specifics and advanced semantic insights to enhance classification accuracy.

2.3 Other Techniques

- KNN Classifier: K-Nearest Neighbors (KNN) stands as a non-parametric machine learning algorithm that categorizes data points by comparing them to labeled neighbors in the training dataset based on their similarity. Utilizing feature extraction methods such as CNNs in conjunction with KNN can offer a straightforward and efficient approach for diabetic retinopathy (DR) classification.
- RTNet (Relation Transformer): This method utilizes a transformer-based deep learning architecture specifically designed for DR lesion segmentation. Transformers excel at capturing long-range dependencies within data, which can be beneficial for identifying complex relationships between different lesion types in retinal images.
- Xception + DeepLabv3: This approach combines Xception, a CNN architecture, with DeepLabv3, a network proficient in semantic segmentation. Here, Xception extracts features, and DeepLabv3 segments the retinal image, potentially identifying regions corresponding to specific DR lesions.
- WT-Swin, WT Attention-Db5: These techniques utilize different adaptations of the Swin Transformer structure, a robust deep learning model designed for image classification. The WT Attention-Db5 block is specifically designed to extract intricate details from high-frequency areas of the image through Discrete Wavelet Transform (DWT), which could potentially assist in identifying subtle features of diabetic retinopathy.

2.4 Ensemble Learning

- Ensemble (EfficientNet-B4, EfficientNet-B5, SE-ResNeXt50): This approach leverages ensemble learning, where multiple pre-trained models like EfficientNet-B4 and SE-ResNeXt50 are combined. By aggregating the predictions from these models, ensemble learning can potentially improve classification accuracy and robustness compared to relying on a single model.

The research under review emphasizes the continuous investigation and advancement of various machine learning methods to address the task of automated diabetic retinopathy detection and classification.

3. Related works

Numerous recent investigations have delved into a variety of machine learning methods for the automated detection and classification of diabetic retinopathy (DR). This review encompasses a range of these studies, focusing on the techniques utilized, datasets employed, and the performance outcomes achieved.

Luo et al.[1] in 2022 investigated the use of Inception V3 networks for diabetic retinopathy (DR) detection. They trained their model on a large dataset of fundus images, combining 1200 color images from the Messidor dataset with 88,702 color images from the EyePACS dataset. With a precision of 93.5% and an Area Under the Curve (AUC) of 0.981, this method showcases the effectiveness of utilizing Inception V3 networks in automated diabetic retinopathy (DR) detection.

Ali et al. [2] in 2023 explored the potential of combining pre-trained deep learning models for detection and classification of DR. Their approach utilized a combination of ResNet50 and InceptionV3 architectures. This method was tested on a dataset comprising 44,119 fundus images sourced from a research study titled "Automatic screening for DR in interracial fundus images using AI." The approach delivered an accuracy of 96.85% and a precision of 96.46%, showcasing the potential of utilizing pre-trained models for automated diabetic retinopathy analysis.

Kalyani et al. [3] explored the potential of Capsule Networks (CapsNets) for diabetic retinopathy (DR) identification. Their approach achieved an accuracy of 98.64% and an F1 score of 97.19% on the Messidor dataset containing 1200 RGB fundus images. CapsNets offer advantages over traditional CNNs by explicitly modeling object-part relationships within an image. This property might be particularly beneficial for DR classification, where identifying and differentiating subtle features like microaneurysms and hemorrhages is crucial for accurate diagnosis. The high performance achieved by Kalyani et al. suggests that CapsNets warrant further investigation for DR detection and classification tasks.

Bilal et al. [5] explored a technique that combines the strengths of multiple approaches for DR detection and classification. Their method leverages a Convolutional Neural Network (CNN) for feature extraction from retinal images. To potentially reduce the dimensionality of the extracted features while retaining crucial information, they incorporate Singular Value Decomposition (SVD). Finally, they integrate an InceptionV3 network for the final classification task. This combined approach was evaluated on a dataset consisting of EyePACS-1, Messidor-2, and DiaretDB0 images, achieving an accuracy of 97.92%, a precision of 97.44%, and an F1 score of 97.10%. These results suggest that combining CNNs with dimensionality reduction techniques and pre-trained architectures like InceptionV3 can be a promising strategy for accurate DR classification.

Das et al. [4] explored the use of EfficientNet B4 and DenseNet201, both pre-trained convolutional neural networks (CNNs), for detecting diabetic retinopathy (DR) in retinal fundus images. They trained their models on the Kaggle's EyePACS, a large dataset of fundus images. While the achieved accuracy of 76.80% suggests that further optimization might be necessary for these specific models in DR classification, their investigation contributes to the exploration of diverse CNN architectures for this task.

Nur-A-Alam et al. [6] explored a FRCNN architecture with feature fusion for diabetic retinopathy (DR) detection. Faster RCNN is a deep learning model adept at object detection and localization. In this context, it likely aided in identifying specific regions of interest (ROIs) within the retinal image, potentially corresponding to DR lesions like microaneurysms or hemorrhages. The feature fusion technique then combined these ROI-specific features with global image features extracted from a CNN. This approach achieved high performance with an accuracy of 98.58%, a sensitivity of 98.57%, and a specificity of 98.61% across three datasets: DiaretDB1, Kaggle, and DDR. These results suggest that Faster RCNN with feature fusion is a promising technique for automated DR detection.

Özbay [7] introduced an Active Deep Learning Convolutional Neural Network (ADL-CNN) for diabetic retinopathy (DR) detection. This approach leverages active learning strategies, where the model can select the most informative data points for training. Özbay evaluated the ADL-CNN on EyePACS dataset with 35,122 images. The method achieved a high accuracy of 99.66%, demonstrating its effectiveness in identifying DR. Additionally, the ADL-CNN exhibited a sensitivity of 93.76% and a specificity of 96.71%, showcasing a good balance between rightly classifying DR cases and avoiding false positives. These results suggest that ADL-CNN has promising potential for automated DR detection.

Candra et al. [8] explored combination of a Convolutional Neural Network (CNN) with a modified Extreme Learning Machine (MLELM) for automated DR detection and classification. Their approach achieved impressive results, reaching an accuracy of 99.21%, a sensitivity of 99.29%, and a specificity of 99.21% on a combined dataset of DRIVE (44 images) and Messidor (1200 images) fundus images. This suggests that their CNN-MLELM architecture effectively learned robust features from the retinal images, enabling accurate differentiation between healthy and diseased retinas.

Ebrahimi et al. [9] explored the application of convolutional neural networks (CNNs) for diabetic retinopathy (DR) classification using (OCTA) images. Their approach incorporated intermediate fusion, where features extracted from different layers within the CNN architecture were combined. This method was evaluated on the UIC – ANGIOVUE SD OCTA dataset containing images from 136 subjects. The CNN with intermediate fusion scored an accuracy of 92.646%, an Area Under the Curve (AUC) of 91.63%, and a specificity of 94.37%. These results suggest that CNNs with intermediate fusion have the potential for accurate DR classification using OCTA images, although further research might be necessary to improve upon these findings.

Kaur and Kaur [10] explored the application of a K-Nearest Neighbors (KNN) classifier for diagnosing diabetic retinopathy (DR). They evaluated their method on the DIARETDB1 dataset, containing 89 fundus images. The KNN classifier achieved an accuracy of 95%, indicating its ability to correctly classify most images. However, the sensitivity of 92.6% suggests there might be a possibility of missing some DR cases. The specificity of 87.59% indicates a moderate ability to avoid false positives (healthy images classified as DR). These findings suggest that while KNN offers a relatively simple approach for DR diagnosis, further research might be necessary to improve its sensitivity and achieve more robust performance.

Huang et al. [11] explored a deep learning architecture called Relation Transformer (RTNet) for segmenting multiple lesions within retinal images. This task is crucial for identifying and quantifying various DR-related abnormalities. Their RTNet model achieved an Area Under the Receiver Operating Characteristic Curve (AUC_ROC) of 95.34%, demonstrating promising potential for automated DR lesion segmentation. The study evaluated the model on two datasets: IDRiD containing a relatively small set of 81 fundus images and DDR, a much larger dataset with 13,673 images. This evaluation highlights the generalizability of the RTNet approach across datasets of varying sizes.

Shaukat et al. [12] explored deep learning for a different task within DR analysis: lesion segmentation. Their approach utilized a combination of Xception, a convolutional neural network architecture, and DeepLabv3, a network proficient in semantic segmentation. This method aimed to identify and delineate specific regions of the retinal image corresponding to DR lesions, such as microaneurysms or hemorrhages. They evaluated their method on a combination of four datasets (MESSIDOR, IDRID, DIARETDB1, and e-ophtha-EX) containing a total of over 3000 fundus images. The model achieved an impressive accuracy of 97.97% and a precision of 0.99, demonstrating its potential for accurate DR lesion segmentation.

Rasha Ali et al. [13] investigated the potential of Swin Transformer variations. Their study employed WT-Swin and WT Attention-Db5 models on the APTOS 2019 dataset. These models achieved impressive accuracies of 98% (Swin-T) and 97% (Swin-B), highlighting the promise of Swin Transformer architectures for automated DR detection. This finding suggests that further research into fine-tuning these models and exploring their generalizability on other DR datasets is warranted.

Tymchenko et al. [14] explored the ensemble learning for diabetic retinopathy (DR) stage detection. Their approach combined three pre-trained deep learning models: EfficientNet-B4, EfficientNet-B5, and SE-ResNeXt50. This ensemble was trained on a large dataset combining the APTOS 2019 images and the Blindness Detection Dataset, totaling over 13,000 images. The ensemble method achieved an impressive accuracy of 98.6% and a high specificity of 0.991, indicating its effectiveness in classifying DR stages. This study highlights the potential of leveraging multiple pre-trained models to achieve robust performance in DR detection tasks.

Chia et al. [15] explored the utilization deep learning systems for DR detection in a population-specific context. Their study utilized a dataset of 1682 fundus images from an indigenous Australian population. The employed deep learning systems achieved a sensitivity of 98.0% and a specificity of 95.1%, demonstrating promising results for DR detection in this specific demographic. This research highlights the potential of adapting and optimizing AI models for diverse populations to improve generalizability and address potential healthcare disparities.

4. Discussion

The reviewed studies explored a diverse range of machine learning techniques for automated diabetic retinopathy (DR) detection and classification. Convolutional Neural Networks (CNNs) emerged as a prominent approach, with studies employing Inception V3 [1], ResNet50+InceptionV3 [2], CapsNet [3], and various pre-trained CNN architectures [4, 5, 8]. These CNN-based methods achieved high accuracy in DR detection, ranging from 93.5% to 99.21%.

Inception V3 achieved an accuracy of 93.5% and an AUC of 0.981, demonstrating its effectiveness for DR detection [1]. The combination of ResNet50 and InceptionV3 further improved performance, reaching an accuracy of 96.85% and a precision of 96.46% for DR detection and classification [2]. CapsNet also yielded promising results with an accuracy of 98.64% and an F1 score of 97.19% for DR identification [3]. However, EfficientNet B4 + DenseNet201 achieved a lower accuracy of 76.80%, suggesting further exploration or

optimization might be required for this specific combination [4].
Several studies investigated techniques beyond traditional CNNs. Bilal et al. proposed a method combining a CNN with Singular Value Decomposition (SVD) and Inception-V3, achieving an accuracy of 97.92%, a precision of 97.44%, and an F1 score of 97.10% for DR detection and classification [5]. This approach highlights the potential benefits of incorporating dimensionality reduction techniques alongside deep learning models.
Another direction involved techniques for feature fusion or exploring alternative architectures. Nur-A-Alam et al. employed Faster RCNN with feature fusion for DR detection, achieving high accuracy (98.58%), sensitivity (98.57%), and specificity (98.61%) [6]. Özbay utilized an Active Deep Learning CNN (ADL-CNN) for DR detection, achieving impressive sensitivity (93.76%) and accuracy (99.66%) [7]. These studies suggest that incorporating strategies to exploit complementary information from different image regions or exploring alternative deep learning architectures can be valuable for DR analysis.
Ebrahimi et al. investigated a CNN with intermediate fusion for OCTA image classification in the context of DR [9]. Their method achieved promising results (accuracy: 92.646%, AUC: 91.63%, specificity: 94.37%), indicating the potential of deep learning for analyzing alternative imaging modalities beyond traditional fundus photography.
While CNN-based approaches dominated the survey, other techniques were also explored. Kaur and Kaur employed a KNN classifier for DR diagnosis, achieving an accuracy of 95% [10]. Huang et al. utilized a Relation Transformer (RTNet) for DR multi-lesion segmentation, achieving an AUC_ROC of 95.34% [11]. Shaukat et al. employed Xception with DeepLabv3 for DR lesion segmentation, reporting an accuracy of 97.97% and a precision of 0.99 [12]. These studies showcase the ongoing exploration of diverse machine learning techniques for various DR-related tasks, such as lesion segmentation.
More recent works have delved into deep learning advancements. Rasha Ali et al. investigated variations of the Swin Transformer architecture for DR detection, achieving accuracies of 98% and 97% [13]. Tymchenko et al. proposed an ensemble approach using EfficientNet architectures for DR stage detection, achieving an accuracy of 98.6% and a specificity of 0.991 [14]. Chia et al. explored deep learning systems for DR detection in a specific population, achieving a sensitivity of 98.0% and a specificity of 95.1% on an indigenous Australian dataset [15]. These studies highlight the potential of leveraging cutting-edge deep learning architectures and tailoring models for specific populations to enhance DR detection and classification.

TABLE I. SUMMARY OF RELATED WORKS

Authors, Year	*Technique*	*Task*	*Dataset*	*Results*
Luo et al.[1] 2022	Inception V3 network	DR Detection	Messidor (1200 colour images) EyePACS (88,702 colour images)	Accuracy: 93.5%, AUC: 0.981
Ali et al.[2] 2023	Resnet50 + Inceptionv3	Detection and Classification of DR	44,119 images – ‘‘Automatic	Accuracy:96.85%, Precision: 96.46%

Authors, Year	*Technique*	*Task*	*Dataset*	*Results*
			screening for DR in interracial fundus images using AI''	
Kalyani et al.[3] 2023	CapsNet	DR Identification	1200 RGB fundus images – Messidor dataset	Accuracy:98.64%, F1 Score: 97.19%
Das et al.[4] 2023	EfficientNet B4 + DenseNet201	Detection of DR	Kaggle's EyePACS	Accuracy: 76.80%
Bilal et al.[5] 2022	CNN + SVD + Inception-V3	Detection and Classification of DR	EyePACS-1 (9088 retinal images) Messidor-2 (1748 retinal fundus images) DiaretDB0 (130 fundus images)	Accuracy: 97.92, Precision: 97.44%, F1 Score: 97.10%
Nur-A-Alam et al.[6] 2023	Faster RCNN + Feature fusion	DR Detection	DiaretDB1 (89 images), Kaggle (20,702 images), DDR(42 images)	Accuracy: 98.58%, Sensitivity: 98.57%, Specificity: 98.61%
Özbay[7] 2023	ADL-CNN	Detection of DR	EyePACS (35,122 images)	Sensitivity: 93.76%, Accuracy: 99.66%, Specificity: 96.71%
Candra et al.[8]	CNN+MLELM	Detection and Classification of DR	DRIVE (44 fundus images) Messidor (1200 fundus images)	Accuracy: 99.21%, Sensitivity: 99.29%, Specificity: 99.21%
Ebrahimi et al.[9] 2023	CNN, Intermediate fusion	OCTA Classification of DR	UIC – ANGIOVUE SD OCTA (136 subjects)	Accuracy: 92.646, AUC: 91.63%, Specificity: 94.37%
Kaur and Kaur[10] 2023	KNN Classifier	Diagnosis of DR	DIARETDB1(89 images)	Accuracy: 95%, Sensitivity: 92.6%, Specificity: 87.59%
Huang et al.[11] 2022	RTNet	DR Mutli-Lesion Segmentation	IDRiD Dataset (81 fundus images) DDR Dataset (13,673 fundus	AUC_ROC: 95.34%

Authors, Year	*Technique*	*Task*	*Dataset*	*Results*
			images)	
Shaukat et al.[12] 2022	Xception + DeepLabv3	DR Lesion Segmentation	MESSIDOR (1200 fundus images) IDRID, DIARETDB1, e-ophtha-EX	Accuracy: 97.97%, Precision: 0.99
Rasha Ali et al.[13] 2024	WT-Swin, WT Attention-Db5	DR Detection	APTOS 2019 dataset	Accuracy: 98%(Swin-T) Accuracy: 97%(Swin-B)
Tymchenko et al.[14] 2020	Ensemble (EfficientNet-B4, EfficientNet-B5, SE-ResNeXt50)	DR Stage Detection	APTOS 2019 Blindness Detection Dataset (13000 images)	Accuracy: 98.6% Specificity: 0.991
Chia et al.[15] 2024	Deep Learning Systems	Detection of DR	Indigeneous Australian dataset(1682 images)	Sensitivity: 98.0% Specificity: 95.1%

5. Conclusion

This survey has explored the landscape of machine learning approaches employed for detecting and classifying DR. The reviewed studies showcase significant progress in this field, with Convolutional Neural Networks (CNNs) emerging as a prominent approach achieving high accuracy. Techniques like Inception V3, ResNet50+InceptionV3, and CapsNet have demonstrated promising results.

However, the field is actively exploring diverse avenues beyond traditional CNNs. This includes methods incorporating feature fusion, alternative deep learning architectures like Swin Transformers, and even the application of deep learning to analyze alternative imaging modalities such as OCTA.

The ability to tailor models for specific populations, as demonstrated by studies using indigenous Australian datasets, further highlights the potential for improving generalizability and addressing healthcare disparities.

Looking forward, the continuous exploration of cutting-edge deep learning advancements and the integration of diverse techniques hold immense promise for the future of DR detection and classification. As these AI-powered systems evolve, they have the potential to revolutionize diabetic retinopathy screening by enabling earlier diagnoses, improving treatment outcomes, and ultimately contributing to the fight against vision loss.

Conflict of interest **The authors declare that they have no conflict of interest.**

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