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Deep learning for early Parkinson's detection: A review of fundus imaging approaches

Abstract

Parkinson's disease (PD), a type of neurodegenerative disease, is on the rise globally as the population ages. Today's costly diagnostic techniques for Parkinson's disease often detect the illness after significant brain damage has already occurred. Early detection is essential for improving patient outcomes and potentially slowing the disease's progression. One of the newest advances in artificial intelligence, deep learning (DL), presents new opportunities for the early, non-invasive diagnosis of Parkinson's disease. Fundus imaging, which captures fine-grained images of the retina, is a promising technique for detecting the disease's early symptoms. Changes in the retinal blood vessels and anomalies of the optic disc (OD) have been linked to neurodegeneration. DL models can identify subtle patterns in these fundus images, such as vascular alterations and changes in the optic disc, which have been connected to Parkinson's disease. This approach replaces current diagnostic methods with a scalable and cost-effective solution, increasing access to early detection. This review explores the current state of the art in using DL models with fundus images to detect PD early on, with a focus on significant public datasets, methodologies, and related research. It highlights how DL models could transform PD screening and provides an overview of the advancements and challenges in this emerging field.

1. INTRODUCTION

PD is a progressive neurodegenerative disease that primarily affects motor function due to the degeneration of dopamine-producing neurons in the brain (Valmarska, 2020). By the time PD symptoms manifest clinically Tolosa et al. (2021) Significant neuronal loss has typically already occurred Shin et al. (2021)making early detection a key goal to improve treatment outcomes (Rumman et al., 2018). Currently, diagnosis is often based on clinical symptoms Tolosa et al. (2021) but only after extensive damage to the nervous system S. Paul et al. (2022) leading researchers to explore alternative methods for earlier detection of PD (Subramaniam et al, 2023).

One promising method for the early detection of neurodegenerative diseases such as Parkinson's disease is fundus imaging, a non-invasive method of taking high-resolution images of the retina. Since the retina is an extension of the central nervous system, changes in its structure could be a sign of neurodegenerative processes in the brain (Robbins et al., 2021). Retinal thinning 8, retinal nerve fiber layer changes Tugcu et al. (2020) and retinal vascular abnormalities Deng et al. (2022) have all been found in PD studies; they may all be early signs of the disease (G. Paul & Elabi, 2022). Due to the difficulty of manually detecting these subtle changes, automated image analysis techniques are required (Hussain et al., 2023).

Using fundus image analysis, DL models have been successfully used to treat ocular diseases such as glaucoma and diabetic retinopathy (Richardson et al, 2024). Automated Image Analysis Kaur et al. (2021) has benefited greatly from recent developments in DL and ML techniques. These techniques help process large data sets, correlations, and complex patterns that are invisible to the naked eye. Because they can efficiently deal with nonlinear and nonstationary problems, DL methods are particularly useful for studying intricate features in medical images. DL models have been efficiently applied to treat ocular diseases including diabetic retinopathy and glaucoma (Aziz et al., 2023; Kako & Abdulazeez, 2022). These models show promise for early disease detection through automated detection and fundus image analysis. These models automatically detect early disease by accurately quantifying and identifying pathogenic changes in retinal images. The use of DL for PD detection by fundus imaging represents a novel approach to detect retinal biomarkers associated

with neurodegeneration before the onset of clinical symptoms. Research has already shown that DL can increase diagnostic accuracy Józwik et al. (2024) and improve the feasibility of incorporating retinal image analysis into regular clinical assessments and Machrowska et al. (2024).

This review examines for the first time the relationship between fundus imaging and DL in the context of PD. We discuss the neurological implications of retinal changes in PD as well as recent advances in automated image analysis. We also look at how DL models are being used on fundus images to help detect PD earlier. We discuss the state of the research, the barriers to integrating this technology into clinical practice, and how these models could revolutionize PD screening. By facilitating timely intervention and potentially delaying disease progression, the early detection provided by these methods may improve patient outcomes. The following sections of the paper are organized as follows: Section 2 explains the methods used. Section 3 provides information about the fundus image datasets. Section 4 outlines related work, and Section 5 focuses on challenges and limitations.

2. METHODOLOGIES

Preprocessing is Critical to the Reliability and Accuracy of DL Models for PD Detection in Fundus Imaging (Li et al., 2021). Retinal images require enhancements to standardize illumination, contrast, and resolution. This helps to detect vascular abnormalities Lu et al. (2021) and OD changes that may indicate PD-related neurological deterioration (Kako et al., 2024). Segmentation isolates key retinal structures such as OD and blood vessels to detect morphologic changes (Shah et al, 2024). Normalization ensures color and intensity consistency across photo sources (Mayya et al., 2023). Artifact removal removes distractions such as dust and reflections. Rotation, flipping, and cropping are used to augment a smaller medical imaging dataset for an effective DL model. Finally, ROI extraction helps DL models work accurately by focusing computational resources on retinal areas most likely to be altered by PD. These preprocessing steps enable reliable and interpretable DL applications for early detection of PD.

3. FUNDUS IMAGE DATASETS

The use of fundus images has become increasingly important in the detection and diagnosis of various ophthalmic diseases, such as diabetic retinopathy, glaucoma, and age-related macular degeneration. As a result, several fundus image datasets have been assembled to help researchers develop and test image analysis algorithms. These datasets vary in size, number of healthy and diseased cases, and type and severity of disease. Table 1 provides a summary of these datasets for easy comparison and selection for specific research purposes.

Tab. 1. Summary of fundus image datasets

Dataset and reference	Full name	Purpose	No. of images	Image resolution	Focus	PD labled	Source/Institution
DRIVE (G. Y. Kim et al., 2021)	Digital Retinal Images for Vessel Extraction.	Diabetic Retinopathy and Vessel Segmentation.	40	768 x 584	Retinal Vessel Segmentation.	No	University Medical Centre Utrecht,
STARE (S Chorage et al., 2016)	Structured Analysis of the Retina.	Retinal disease diagnosis, vessel segmentation.	20	700 x 605	Retinal vessel segmentation.	No	Shiley Eye Centre, University of California,
APTOS (Escorcia-Gutierrez et al., 2022)	Asia Pacific Tele-Ophthalmology Society.	Diabetic Retinopathy Diagnosis.	3,662	2048 x 1536	Diabetic Retinopathy Classification.	No	Kaggle/AsiaPacific Tele-Ophthalmology Society,
REFUGE (Orlando et al., 2020)	Retinal Fundus Glaucoma Challenge.	Glaucoma detection.	1,200	2124 x 2056	OD and Cup Segmentation.	No	REFUGE Challenge,
MESSIDOR-2(J. Kim et al., 2018)	Methods to Evaluate Segmentation and Indexing Techniques in the Field of Retinopathy.	Diabetic retinopathy analysis.	1,200	1440 x 960	Diabetic Retinopathy.	No	French National Institute for Research in Computer Science
Kaggle DR Detection (Pradhan et al., 2020)	Kaggle Diabetic Retinopathy Detection.	Diabetic retinopathy detection.	35,126	Varies	Diabetic Retinopathy.	No	Kaggle DR.
EyePACS (delaPava et al., 2021)	Photo-Assessment Collaboration Study.	Diabetic Retinopathy Detection.	88,702	Varies	Diabetic Retinopathy Screening.	No	EyePACS/Kaggle.

Tab. 1. Summary of fundus image datasets, continued

Dataset and reference	Full name	Purpose	No. of images	Image resolution	Focus	PD labled	Source/Institution
IDRiD (Porwal et al., 2018)	Indian Diabetic Retinopathy Image Dataset.	Diabetic retinopathy analysis.	516	4288 x 2848	Retinal Lesion Segmentation.	No	Indian Institute of Technology (IIT)
RIGA (Alghamdi & Abdel-Mottaleb, 2021)	Retinal Fundus Images for Glaucoma Analysis.	Glaucoma Detection.	1,196	2144 x 1424	OD and Cup Segmentation.	No	RIGA.
AREDS (Ruamviboonsuk et al., 2021)	Age-Related Eye Disease Study.	Age-related macular (AMD) degeneration research.	17,825	6000 x 4000	AMD severity, grading, and lesions.	No	National Eye Institute, USA
DRIONS-DB (Mohan et al., 2018)	Digital Retinal Images for Optic Nerve Segmentation.	Optic Nerve Segmentation for Glaucoma Detection.	110	600 x 400	Optic Nerve Head Segmentation.	No	University of Zaragoza
RIM-ONE (Shoukat et al., 2021)	Retinal Image Database for Optic Nerve Evaluation.	Glaucoma Screening.	159	2144 x 1424	Optic Nerve Head, Glaucoma Screening.	No	University of Valladolid
HRF (Han et al., 2022)	High-Resolution Fundus.	Retinal Vessel Segmentation.	45	3504 x 2336	Retinal Vessel Segmentation.	No	University of Erlangen, Germany
SABRE (van Leeuwen, 2003)	Southall and Brent Revisited.	Cardiovascular and Metabolic Risk Study.	2000	3872 x 2592	Retinal Imaging for Cardiovascular Risk.	No	Imperial College London
CHASE__DB1 (Memari et al., 2019)	Child Heart and Health Study in England Database 1.	Vessel Segmentation.	28	999 x 960	Vessel Segmentation.	No	Kingston University
UK Biobank (Han et al., 2022)	UK Biobank.	General Retinal Imaging for Genetic Studies.	500,000	5000 x 3500	General Eye Disease, Retinal Imaging.	Yes (Potentially)	UK Biobank
PALM (Y. Sun et al., 2023)	Pathologic Myopia Challenge.	Myopia Detection.	400	Varies	Pathologic Myopia Detection.	No	PALM Challenge
LES-AV (Yoga Sri Varshan et al., 2023)	Longitudinal Evaluation of Stereoscopic Images for Arteriovenous Ratio.	Vessel Segmentation and AVR Measurement.	22	768 x 576	Arteriovenous Ratio Measurement.	No	University of California
GAMMA (Bajwa et al., 2020)	Glaucoma Grading from Multi-Modality Images.	Glaucoma Grading and Detection.	1,020	1536 x 1024	Optic Nerve Grading.	No	GAMMA Challenge, Sun Yat-sen University

4. RELATED WORKS

Maninis et al. (2016) presented a novel DL, called Deep Retinal Image Understanding DRIU, for segmenting blood vessels and optic discs in retinal images. The approach outperforms other current methods for the same tasks.

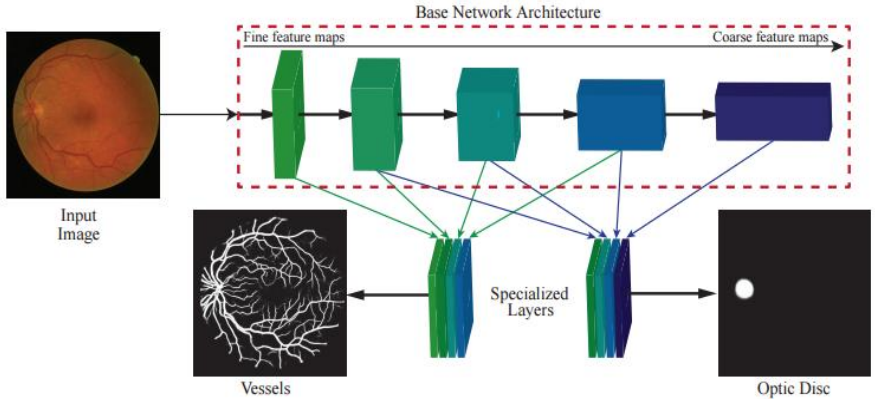

Fig. 1. Illustrates the approach of DRIU, where specialized layers are designed to segment blood vesselson the left and optic discs on the right by extracting feature maps from a base Convolutional Neural Network (CNN) (Maninis et al., 2016)

Khalil et al. (2019) discussed the use of CNN to classify types of diabetic retinopathy.

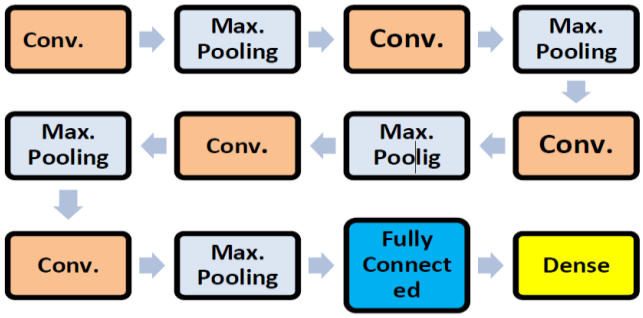

Fig. 2. Depicts the block diagram of the proposed system as described in (Khalil et al., 2019)

Jebaseeli et al. (2019) discusses a proposed method for retinal image analysis to detect diabetic retinopathy and compares its performance with other methods. It also mentions various retinal image segmentation tools available for diagnosis and an Android system developed for limited use.

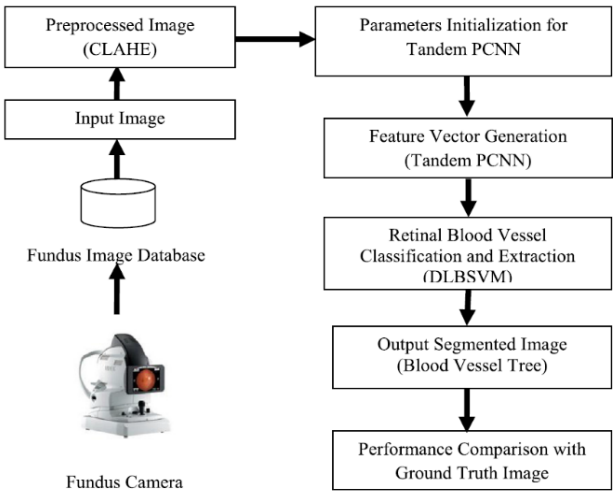

Fig. 3. Retinal blood vessels segmented from real-time clinical images collected at the hospital (Jebaseeli et al., 2019)

Memari et al. (2019) discussed performance measures and preprocessing for matched filtering-based retinal vessel segmentation.

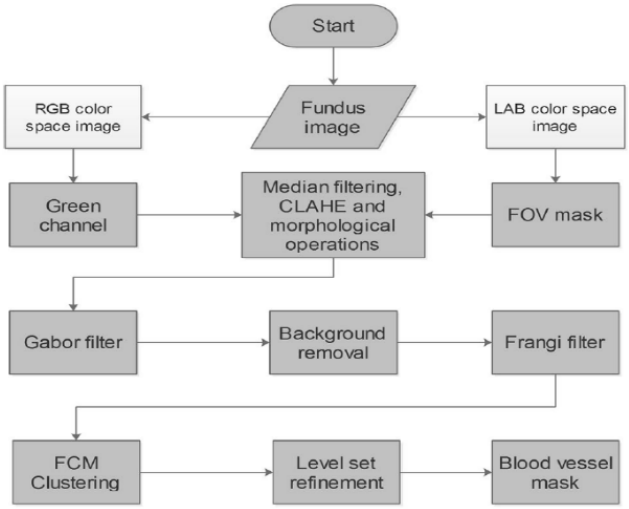

Fig. 4. Illustrates the flowchart of the proposed vessel segmentation method (Memari et al., 2019)

Martinez-Perez et al. (2019) focused on the use of retinal imaging to detect diabetic retinopathy in patients.

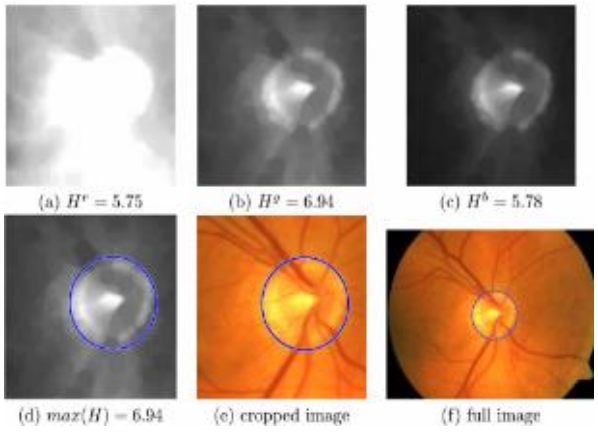

Fig. 5. Illustrates the analysis of information content and the application of the Circular Hough Transform (CHT) on an image featuring a saturated red channel (Martinez-Perez et al., 2019)

X. Wang et al. (2019) Discuss a new method for segmenting retinal blood vessels using multiple feature extraction techniques and dimensionality reduction.

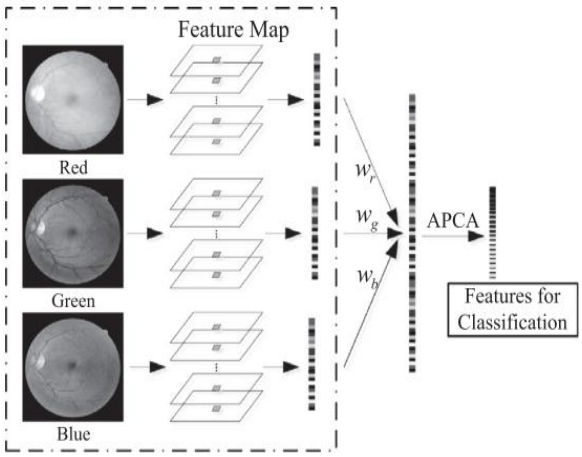

Fig. 6. Flowchart illustrating feature extraction, color channel fusion and dimensionality reduction (X. Wang et al., 2019)

Diaz et al. (2020) explored the possibility of diagnosing PD using non-invasive fundus images of the eye and achieved promising results using machine learning and vessel segmentation techniques.

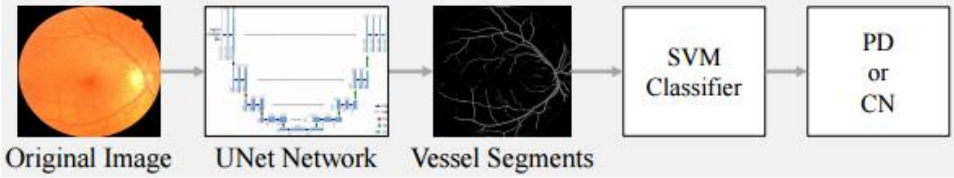

Fig. 7. RGB Image Network Flow (Diaz et al., 2020)

El-Hag et al. (2021) discussed techniques for diagnosing retinal disease, including approaches for detecting optic discs in color fundus images, classifying retinal images, and segmenting blood vessels.

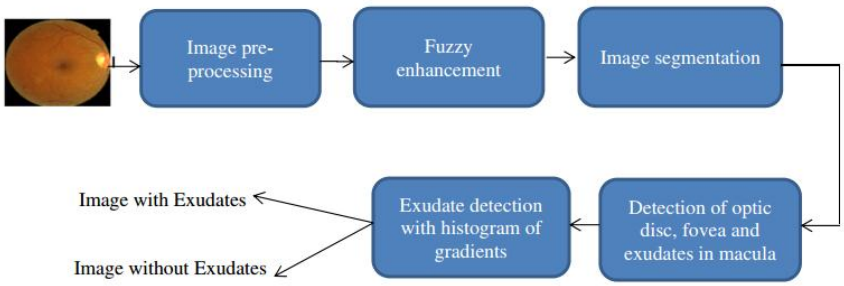

Fig. 8. A block diagram illustrating the stages of diabetic maculopathy detection (El-Hag et al., 2021)

Dai et al. (2021) presented a study combining DL algorithms and human primary hepatocytes to improve prediction of drug-induced liver injury.

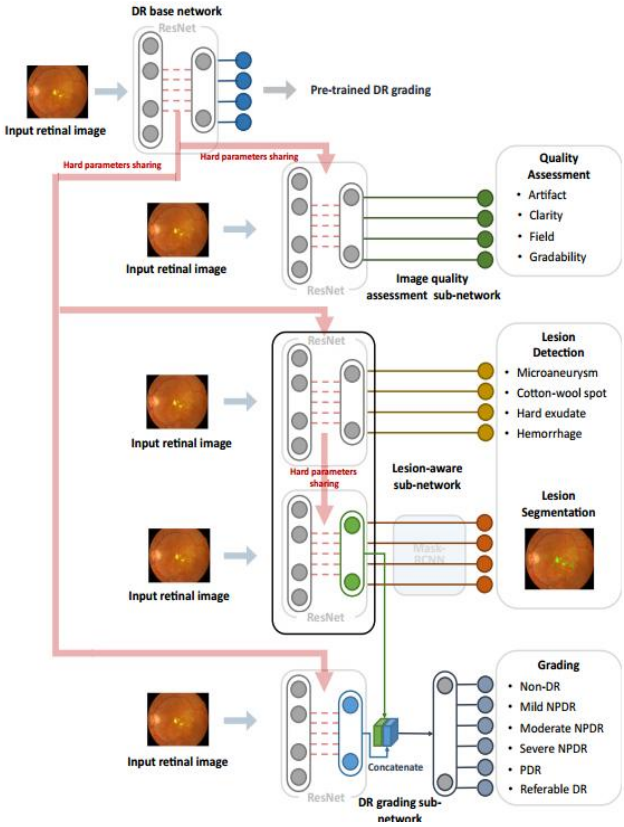

Fig. 9. A visual representation of the DeepDR system (Dai et al., 2021)

Zhang et al. (2021) discussed retinal imaging techniques for the recognition and prediction of mild cognitive impairment using machine learning models.

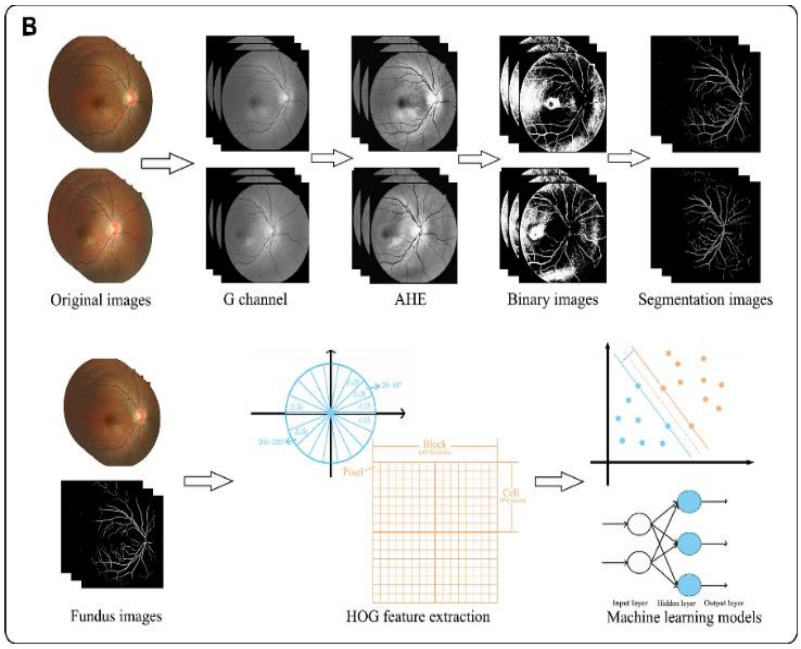

Fig. 10. A visual summary of the study (Zhang et al., 2021)

Zhou et al. (2022) presented a novel approach to analyze retinal images for systemic disease insights, known as "oculomics" using confidence analysis to increase reliability.

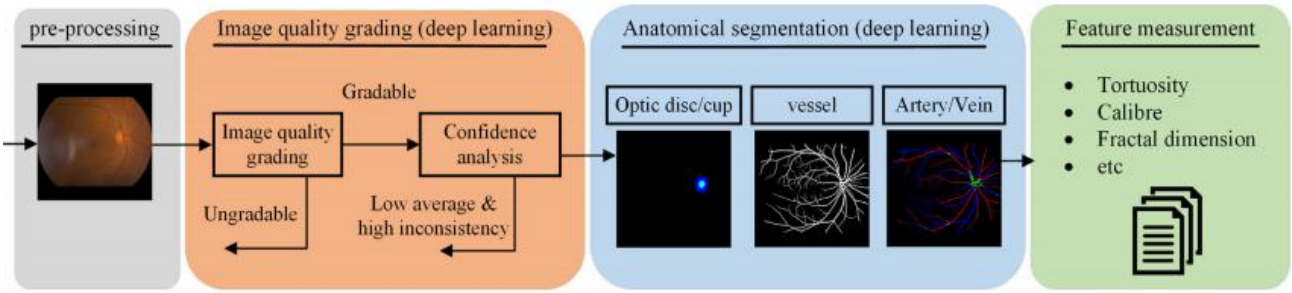

Fig. 11. AutoMorph uses DL models for the image quality grading and anatomical segmentation of colored fundus photographs (Zhou et al., 2022)

Ahn et al. (2023) used DL to predict PD severity based on fundus images and clinical data.

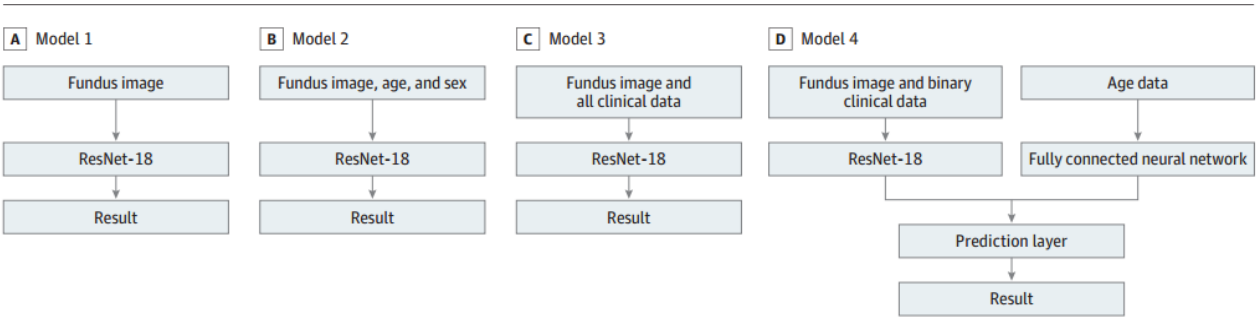

Fig. 12. DL systems can be classified into four categories (Ahn et al., 2023)

Sun et al. (2023)] discussed the use of artificial intelligence and DL in the diagnosis of retinal and optic nerve diseases using ultra-widefield retinal imaging.

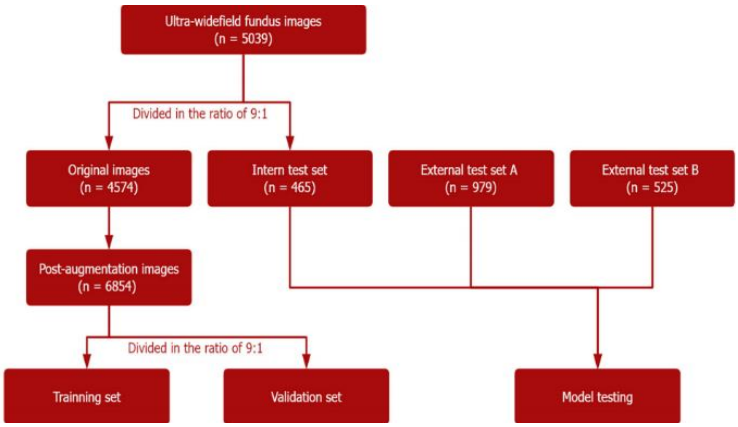

Fig. 13. Workflow illustrating the development of the DL model for recognizing multiple diseases in Ultra-widefield Images (UWFI) (G. Sun et al., 2023)

Arslan et al. (2023) discussed the importance of comprehensible DL methods in medical applications and their potential benefits.

Pitchumani Angayarkanni and Kolengadan (2024) discussed the diagnosis and feature extraction related to PD using different techniques and models.

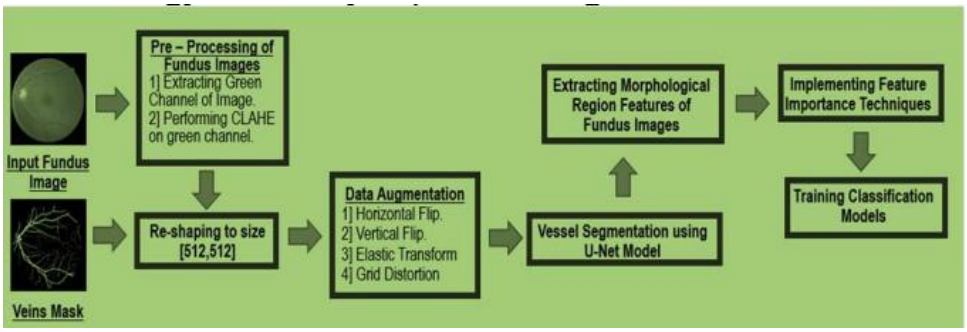

Fig. 14. Process Workflow (Pitchumani Angayarkanni & Kolengadan, 2024)

Tran et al. (2024) provided a machine learning model for PD diagnosis, implemented with various image rotation and augmentation techniques.

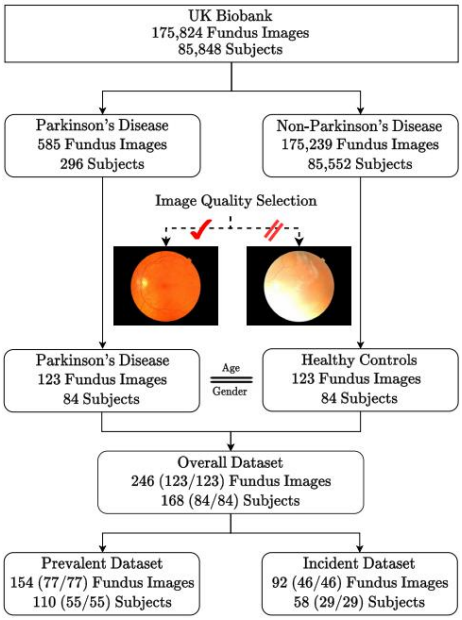

Fig. 15. Illustrates the UK Biobank data collection pipeline, which includes quality selection and subject matching for both PD and healthy controls (Tran et al., 2024)

Wang et al. (2024) discussed a novel method for predicting cardiovascular disease using retinal fundus image analysis. It provides a reliable method for screening vascular aging, especially in undeveloped areas.

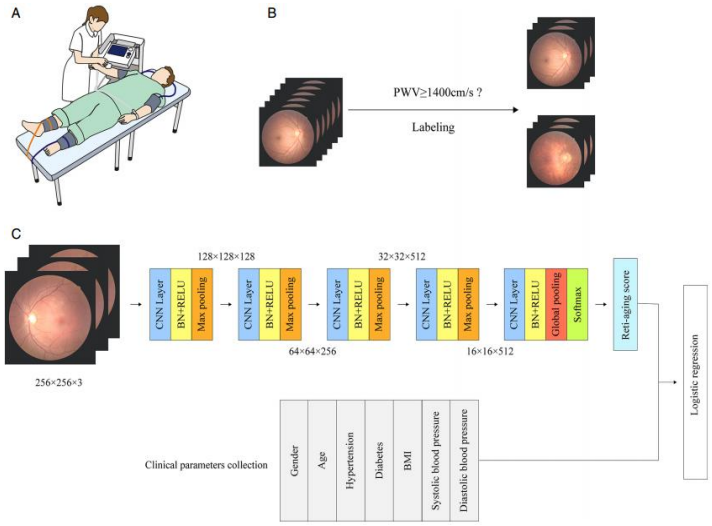

Fig. 16. Overview of DL model development: (A) Pulse Wave Velocity (PWV) examination method, (B) Image labelling by PWV, (C) Model construction and comparison of Reti-ageing score with clinical parameters (Wang et al., 2024)

Tab. 2. Comparative performance metrics of DL models

Reference	Used dataset	Classifier	Methodology	Feature type	Performance	Output
(Maninis et al., 2016)	DRIONS-DB, RIM-ONE, DRIVE & STARE.	CNNs	GoogLeNet	Feature maps.	Achieves superior performance.	Retinal vessel. OD segmentation.
(Khalil et al., 2019)	ARIA, STARE & DRIVE.	CNN	CNN	Visual feature (fovea, blood vessels, and optic disc)	Accuracy = 95.23%	Normal. Non-proliferative diabetic retinopathy (NPDR). Proliferative diabetic retinopathy (PDR).
(Jebaseeli et al., 2019)	DRIVE, STARE, HRF, REVIE & DRIONS	DLBSVM & PCNN	Combines DL, image processing, and ML techniques	Feature vectors	Accuracy = 99.16%, sensitivity = 74.45% specificity = 99.40%	Classification of the retinal blood vessels Extraction of the retinal blood vessels
(Memari et al., 2019)	DRIVE, STARE, & CHASE_DB1		Fuzzy C-Means (FCM) & Integrated level set	Feature vectors	Accuracy of 0.961, 0.951 & 0.939 in DRIVE, STARE, & CHASE_DB1	Extract the retinal blood vessel network while reducing noise
(Martinez-Perez et al., 2019)	SABRE, DRIVE & MESSIDOR.	CHT algorithm		OD (circular shapes)	Accuracy = 0.994, TPR = 0.879, FPR = 0.003, Overlap = 80.6% & Dice index = 0.878	Detect the shape of the optic disc.
(X. Wang et al., 2019)	DRIVE, STARE & CHASE_DB1	Cascade classification network	PCA, Mahalanobis classifier	Matched filter, 2-D Gabor wavelet, grey-level-based, Firangi filter & Difference of Gaussian.	Accuracy = 95.41–96.40%	Retinal vessel segmentation

Tab. 2. Comparative performance metrics of DL models, continued

Reference	Used dataset	Classifier	Methodology	Feature type	Performance	Output
(Diaz et al., 2020)	UKB & UF-UKB	SVM	U-Net segmentation	Retina vasculature (smaller blood vessels)	Accuracy = 85%	PD Healthy
(El-Hag et al., 2021)	STARE, DRIVE, DRIONS & HRF.	Fuzzy preprocessing, gradient process & CNN	CNNs	Optic, blood vessels, fovea, exudates	Accuracy = 100%, Sensitivity = 95%, Specificity = 100%	Detection of exudates in retinal images
(Dai et al., 2021)	Local: SIM, CNDCS & NDSP; publicly: EyePACS	Mask R-CNN and ResNet	DeepDR	Multiscale features	AUC = 0.955	Automated grading of diabetic retinopathy.
(Zhang et al., 2021)	Private dataset	SVM & ELM	Extracting image features and training ML models	HOG feature	AUCs training set = 0.87, 0.88 & 0.90	Automated detection of diabetic retinopathy.
(Zhou et al., 2022)	EyePACS-Q, DRIVE, STARE, CHASEDB1, HRF, IOSTAR, LES-AV, REFUGE, GAMMA, and IDRID.	DCNNs	DL and confidence analysis	Multiple features from the fundus images	F1-score = 0.86	AutoMorph—an automated method for quantifying retinal vascular morphology.
(Ahn et al., 2023)	Independent hospital data sets (615 participants)	CNN as part of a multimodal network along with a fully connected neural network.	DL with CNNs.	Features from the fundus images	Accuracy = 70.45, AUROC = 0.67	PD non-PD
(G. Sun et al., 2023)	UWFIs of patients from Renmin Hospital	EfficientNet-B7, DenseNet, ResNet-101, ImageNet	ImageNet	Heatmap Features	Accuracy = 93.00%	Fundus disease classification on UWFI.
(Arslan et al., 2023)	Private dataset	CNN	CNNs, GradCAM++, CAM, XGradCAM, and GradCAM.	Macular	Accuracy = 70.5%, sensitivity = 80%, and specificity = 67%. AUC-ROC = 0.67	Disease severity in the case of PD
(Pitchumani Angayarkanni & Kolengadan, 2024)	retinal-fundus-images, DRIVE	Random Forest, Gradient Boosting, AdaBoost, XGBoost, MLP, SVC, Decision Tree, KNN, Stack, Ensemble & Bagging Classifier.	SHAP	Morphological features	Accuracy = 97.17%, F1-score = 0.9716, sensitivity = 0.9529, specificity = 0.9824, AUC-ROC = 0.9937, PPA = 0.9687, NPA = 0.9733, precision = 0.9687 & recall = 0.9529	PD non-PD
(Tran et al., 2024)	UK Biobank	SVM (RBF)	Inference with Machine Learning (IML) framework.	Various feature engineering	Accuracy = 68%	PD non-PD
(Wang et al., 2024)	2 independent datasets	DL & Regression.	logistic regression analysis.	Feature maps	Accuracy = 66.3%	Predict vascular ageing.

5. CHALLENGES AND LIMITATIONS

Although DL models using fundus images show promising results for PD detection, several major challenges remain to be addressed. Important challenges include the development of more robust model architectures, lack of protocol standardization, and variability of data sets. Detection of early-stage PD-when retinal changes are minor-remains a challenging task, even though many models have demonstrated high sensitivity and specificity. In addition, bias from training datasets and model generalizability greatly influence how well these algorithms perform in real-world clinical settings. Research initiatives must focus on overcoming these challenges, in particular by diversifying training datasets, improving model sensitivity and specificity, and building interpretable artificial intelligence systems, thereby increasing transparency and trust in AI-assisted diagnosis.

6. DISCUSSIONS

The reviewed studies show the great promise of DL models for fundus imaging in early detection of PD. Retinal features necessary for the identification of neurodegenerative changes associated with PD have been analyzed in the literature using several approaches, including vascular segmentation, morphologic changes, and OD localization. These studies have advanced automated retinal image analysis using DL techniques, providing a more efficient and less error-prone replacement for conventional manual assessment approaches.

Using CNNs, Maninis et al. (2016) presented the DRIU framework for accurate automated segmentation of retinal vessels and optic discs. This structure achieves accuracy beyond human knowledge. To improve the scalability of ophthalmic diagnostics, the DRIU framework resolves class imbalance using a balanced loss function and runs at a speed suitable for real-time clinical use.

Additionally, a CNN model with an accuracy rate of 95.23% was developed to classify fundus images for DR, El-Hag et al. (2021). This model effectively identifies significant markers, including microaneurysms and hemorrhages, thus illustrating the diagnostic ability of CNNs for ocular diseases. However, further research is needed to investigate their potential for the identification of PD.

Jebaseeli et al. (2019) segmented retinal blood vessels in diabetic retinopathy using a mixture of Tandem Pulse Coupled Neural Network (TPCNN) and Deep Learning-Based Support Vector Machine (DLBSVM) with an impressive accuracy of 99.16%. Their method captures fine blood vessel details better than accepted supervised methods. Memari et al. (2019) instead used mathematical morphology, matched filtering, and fuzzy c-means clustering to separate retinal vessels. Although their method has high accuracy, it does not use deep learning, which suggests a possible gap in PD detection that could be explored by combining DL methods.

Martinez-Perez et al. (2019) developed an OD detection method with better accuracy than single-channel methods using multispectral analysis. X. Wang et al. (2019) proposed a cascade classification system for retinal vessel segmentation to achieve high segmentation accuracy, which is suitable for other image recognition tasks. Although hopeful, further studies are needed to show how accurately these models detect early PD.

In a major advance in non-invasive PD diagnosis, Diaz et al. (2020) explored machine learning (ML) PD classification based on retinal vessel patterns. Using CNNs, El-Hag et al. (2021) also created a framework for maculopathy detection, providing a benchmark for the next applications of DL in PD detection. Demonstrating the flexibility of such systems for PD detection, Dai et al. (2021) presented DeepDR, a transfer learning based network for diabetic retinopathy detection.

Zhang et al. (2021) identified cognitive decline using retinal imaging techniques; therefore, related studies for PD could be considered using similar methods. Zhou et al. (2022) presented a fully automated pipeline for assessing retinal vascular geometry in PD detection, showing great performance over many datasets. Ahn et al. (2023) highlighted the possibilities for non-invasive clinical assessment by evaluating neurological dysfunction in PD patients using DL models based on fundus images.

Sun et al. (2023) developed a DL model using ultra-widefield images to detect fundus diseases with accuracy equivalent to experienced physicians, suggesting that similar models could be tuned to detect PD early. Arsalan et al. (2023) investigated deep learning-based PD assessment with high sensitivity and specificity using retinal images with high clarity. Promising non-invasive diagnostics, Pitchumani Angayarkanni and Kolengadi (2024) presented a model for PD detection in AMD images.

Using the UK Biobank dataset, Tran et al. (2024) evaluated DL and machine learning methods, laying the foundation for fundus imaging-based PD detection. Finally, Wang et al. (2024) demonstrated the widespread

use of DL in retinal fundus imaging for many medical conditions, suggesting that these methods can be adapted for PD detection.

Taken together, these studies demonstrate the effectiveness of DL approaches applied to fundus imaging as a practical route to early, non-invasive detection of PD. However, several issues remain to be addressed: standardization of protocols, variance in datasets, and improvement of model architecture. Ongoing research will ensure their generalizability and their ability to overcome biases introduced by the training datasets, so that the refinement of these models and the verification of their clinical applicability depend on this process. Overcoming these obstacles will enable DL models to become a necessary tool for early diagnosis and treatment of PD.

7. CONCLUSIONS & FUTURE WORK

In conclusion, the potential of DL for early detection of PD using non-invasive fundus imaging is promising. DL models, especially CNNs, can detect early changes in the retina associated with neurodegeneration. This is an easy-to-use alternative to traditional diagnostic methods, which typically detect PD when it is well advanced. To improve model reliability and diagnostic accuracy, larger and more diverse data sets, improved sensitivity and specificity, and standardized imaging protocols are needed.

Future research must address these challenges by increasing the diversity of datasets and developing tractable AI models to increase clinical confidence in automated diagnosis. Multimodal imaging and transfer learning could improve diagnostic accuracy and expand the applicability of these models to PD and other neurodegenerative diseases. In addition, the development of hybrid artificial intelligence models-those that combine deep learning with traditional machine learning techniques-may improve detection accuracy and resilience. Data fusion-including clinical data and multidimensional fundus images-may provide a more complete knowledge of PD. These additions provide a clear path for future improvements in PD detection using deep learning.

Conflicts of Interest

This work does not have any conflict of interest to declare.

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