Review

Deep Learning and The Retina: A New Frontier in Multiple Sclerosis Diagnosis

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ABSTRACT: Multiple sclerosis (MS) is a chronic autoimmune disease of the central nervous system that leads to neurodegeneration and functional disability. Because recent advances in retinal imaging have revealed that the retina is a non-invasive window into the brain, offering valuable biomarkers for MS diagnosis and progression tracking, we explored the integration of artificial intelligence (AI), particularly deep learning (DL), in the analysis of fundus-based imaging techniques such as Optical Coherence Tomography (OCT), fundus photography, and Scanning Laser Ophthalmoscopy (SLO). These investigations allow for the detection of subtle retinal changes, such as thinning of the retinal nerve fiber layer (RNFL) and ganglion cell-inner plexiform layer (GCIPL), which are closely associated with MS pathology with the help of AI-driven models, including convolutional neural networks (CNNs), generative adversarial networks (GANs), and explainable AI approaches and they have demonstrated high accuracy in classifying MS patients, even at early stages, and predicting disease severity. The review also discusses the challenges and future directions of applying AI in ophthalmic diagnostics, including data standardization, model interpretability, and clinical integration. Overall, AI-enhanced retinal imaging is emerging as a powerful, non-invasive tool that can complement traditional neurological assessments and support earlier, more personalized MS care.

KEYWORDS: *Multiple sclerosis, AI models, deep learning, eye fundus, OCT.*

Introduction

Multiple sclerosis (MS) is a complex autoimmune disease characterized by inflammation, demyelination, neurodegeneration and axonal damage, affecting both the brain and spinal cord [1].

The fundus, through modern imaging methods such as OCT, SLO or fundus photography, can be accurately analyzed using artificial intelligence algorithms, opening new perspectives in early diagnosis and monitoring of the disease [2].

These artificial intelligence algorithms are increasingly valuable among researchers, mostly because they are being used to detect and classify MS-related abnormalities with greater accuracy thus improving efficiency in diagnosis, disease follow-up and personalized treatment planning [3].

The potential of AI to predict MS progression has attracted significant interest, as machine learning (ML) and deep learning (DL) models can analyze long-term imaging data to predict the trajectory of the disease, which can help tailor treatments to individual patients and allow for early interventions that can slow the progression of disability [4].

Diagnosis and monitoring of neuro-ophthalmological and retinal diseases require examination of the fundus.

Indirect ophthalmoscopy is among the available methods that provide detailed visualization of the retina, but has limitations due to the field of view and the need for pupil dilation.

One of the most frequently used technologies in screening for diabetes mellitus and macular degeneration, as it allows objective documentation of retinal lesions is fundus photography, while OCT is ideal for diagnosing glaucoma, macular edema, and AMD, allowing optical sectioning of the retina and analysis of its stratification with amazing accuracy without the need for eye contact or contrast agents [5,6].

In addition, several studies have shown that the use of OCT and fundus photography together significantly increases the accuracy of screening, especially for general populations [7].

Due to the availability of portable equipment, low cost, and ease of use, these two methods are particularly accessible [3].

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For this reason, fundus and OCT continue to be the preferred methods in everyday clinical practice, as they offer an ideal balance between accuracy, accessibility, and non-invasiveness (Table 1).

This scoping review aims to critically and comprehensively evaluate and synthesize the current state of the art in the use of AI-assisted retinal imaging in the diagnosis and monitoring of MS, having three major objectives:

1. Clarifying the current state of the art in automated MS diagnosis using fundus photography and OCT, with a particular focus on ML and DL applications by conducting a detailed analysis of algorithmic architectures, image segmentation strategies, and model performance in detecting retinal biomarkers relevant to neurodegenerative processes, specific for MS [8].
2. Identifying emerging trends and their technological limitations, as well as mapping future research directions regarding the integration of AI in retinal imaging for MS. In this way, we aim to discuss current and future challenges, such as model transferability between platforms, lack of explainability, lack of relevant data, and the need for longitudinal datasets from multiple clinical centers, with a special focus on multimodal AI systems capable of correlating retinal imaging with clinical and neuroimaging data [9].
3. Establishing a scientifically sound optimal time frame for detecting significant structural changes in the retina associated with MS progression, by synthesizing the results obtained from longitudinal studies and formulating recommendations on the optimal frequency of imaging assessments in future clinical trials while highlighting the potential of ophthalmological biomarkers to indicate early neurological deterioration [10].

Material and Methods

This review used scientific manuscripts sourced from an exhaustive literature search on platforms like PubMed and Google Scholar.

Articles were selected based on relevance to MS biomarkers, AI-driven imaging tools, and comparative analyses of manual and automated diagnostic techniques. The search was based on keywords such as “Multiple Sclerosis”, “OCT”, “fundus”, “Deep Learning”, “Machine Learning”, “Artificial Intelligence”, combined using Boolean operators.

Inclusion criteria were limited to English-language articles published in the last decade, thus ensuring contemporary relevance, while other inclusion criteria included studies on fundus imaging in MS and AI methodologies in medical imaging.

Excluded were non-English publications and those unrelated to neurological disease or lacking quantitative transparency (Figure 1).

Table 1. Examination Modalities in MS-Fundus and OCT-Based Techniques.

Title	Brief	Strengths	Weaknesses	Paper
Fundus Photography	2D color imaging of the retina used to detect optic disc pallor and vascular changes in MS	Widely available Low-cost Non-invasive Portable	Lacks depth resolution Subtle changes may be missed	[11]
Time-Domain OCT (TD-OCT)	Early-generation OCT providing retinal cross-sections	Accessible in older clinics Quick scan time	Low resolution Limited layer segmentation	[12]
Spectral-Domain OCT (SD-OCT)	High-resolution structural imaging of RNFL, GCIPL	High sensitivity Good repeatability Correlates with disability scores	Variability between machines Motion artifacts	[2]
Swept-Source OCT (SS-OCT)	Deeper and faster scans than SD-OCT	Visualizes choroid and vitreoretinal interface Improved signal strength	Higher cost Limited availability	[13]
OCT Angiography (OCTA)	Maps retinal and choriocapillaris microvasculature without dye	Non-invasive Detects vascular loss linked to MS	Sensitive to motion Artifacts in low-perfusion areas	[14]
Multimodal OCT + Fundus	Combines structural OCT and en face fundus images	Enhances lesion localization Offers layered and top-view data	Interpretation complexity Alignment challenges	[15]
OCT with Eye Tracking	Adds real-time alignment tools to OCT scanning	Reduces motion error Improves reproducibility in longitudinal scans	Requires advanced device and software	[16]
OCT Combined with BICAMS	Links retinal structure to cognitive performance in MS	Supports multimodal MS phenotyping	May be influenced by cognitive variability	[17]

A manual review of the reference lists from all the identified articles was also conducted to ensure comprehensive coverage of the topic. This narrative review does not follow the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines but maintains a structured approach to article selection, with each manuscript rigorously evaluated by a panel of two independent reviewers.

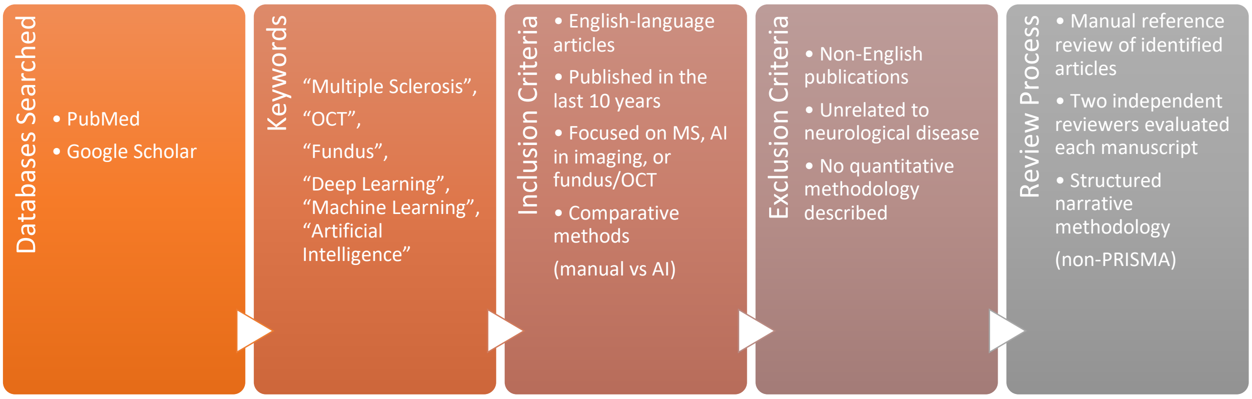

Figure 1. Literature Review Methodology.

Pathophysiology of MS and Fundus Biomarkers

Multiple sclerosis is characterized by immune-mediated self-attacks on the CNS structures, which can cause neurodegeneration and a constant state of systemic inflammation [18].

Neurodegeneration and chronic inflammation erode the myelin sheath, thus destroying the communication between neurons, causing motor and sensory impairments. The retina, which is considered an extension of the brain, can replicate a similar pattern of lesions, making it useful for both initial and long-term monitoring [19].

There are two key retinal biomarkers: the retinal nerve fiber layer (RNFL) and the ganglion cell-inner plexiform layer (GC-IPL) [20].

These markers can be considered windows into the brain's aspect. RNFL thinning is a sign of broader axonal loss, and this loss can be confirmed even in patients without clinically manifested optic neuritis, and the GC-IPL, sensitive to ganglion cell degeneration, can offer proof of cognitive decline and brain atrophy [21].

Imaging methods are a valuable tool that can help physicians quantify these changes and observe the progression of the disease and the response to treatment with high precision, in a non-invasive manner [22].

MRI, which is the gold standard when it comes to imaging techniques in MS, has several disadvantages compared to fundus imaging [23].

First, ophthalmoscopy and OCT are a safer examination method because they do not use contrast agents or radiation exposure, which makes them suitable for a broader category of patients. They are also a better option in terms of financial costs, which makes them suitable for frequent examination without the financial burden of neuroimaging [24].

Several other methods are available for examining the ocular fundus, as presented in Table 1.

OCT is an examination that is capable of obtaining high-resolution images of retinal structures in seconds, offering important and fast details about the integrity of the retinal layer, thus observing in a matter of seconds any new neurodegenerative changes in a patient [25].

There are also numerous studies that show that OCT biomarkers are easy to correlate with the Expanded Disability Status Scale (EDSS), but also with other disability scores, making it an important tool in tracking disease severity [26].

Combining artificial intelligence and OCT imaging is extremely beneficial for MS patients because, due to AI tools, it is easier to detect MS-related abnormalities, to improve diagnostic accuracy, and also easier to identify high-risk patients. With the help of OCT, clinicians can monitor neurodegeneration, they can easily evaluate the response to different kind of treatments and more importantly, they can predict the disability outcome in time. Considering the continuous evolution that AI has, OCT can become more and more important in time and it can become a stability element in a rather unstable and unpredictable disease.

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Deep Learning and Eye Fundus Imaging in MS Diagnosis

Fundus photography is an accessible screening modality that has shown promise when combined with DL algorithms. Recent advances have shown that fundus images can capture even the most subtle retinal changes associated with MS lesions, and when processed by convolutional neural networks (CNNs), these features can be automatically identified with extremely high diagnostic accuracy.

A 2023 study by Roya Arian and colleagues utilizes fundus images, acquired using scanning laser ophthalmoscopy (SLO), and CNNs for the diagnosis of MS. The suggested model, SLO-MSNet, integrates CNNs with a multiclass perceptron (MLP), attaining 88% accuracy, 86% sensitivity, and 91% specificity in the preliminary diagnosis of MS. This model can detect subtle, clinically invisible retinal changes, providing a non-invasive, inexpensive and effective alternative to conventional methods.

This is the first study to use SLO for this purpose, demonstrating the potential of artificial intelligence in fundus analysis for early and accessible diagnosis of MS and suggesting that deep learning applied to fundus photography offers a viable alternative to aid in the diagnosis and monitoring of MS, especially in conditions where more advanced fundus imaging such as OCT is not available [34].

Deep Learning and OCT Imaging in MS Diagnosis

OCT has become a useful tool for the early diagnosis and monitoring of MS because it can provide non-invasive, high-resolution images of retinal structures that reflect neurodegenerative processes, while OCT-derived biomarkers, especially those involving the RNFL and ganglion cell layer, have been shown to be very good at reflecting disease activity and progression. The combination between optical coherence tomography with machine learning and deep learning techniques has improved the efficiency of diagnosis, allowing automated analysis and identification of subtle structural changes that are often overlooked by human clinicians [34,35].

Recent advancements in artificial intelligence have significantly enhanced the utility of retinal imaging, particularly OCT, in the early diagnosis and monitoring of MS. In a 2022 study published by López-Dorado et al. employed SS-OCT in combination with CNNs to detect early MS-related retinal changes. Data limitations were overcomed, by using synthetic training data using GANs, achieving a perfect sensitivity and specificity in distinguishing MS patients from healthy subjects, thus highlighting the potential of AI-powered OCT as a fast, non-invasive diagnostic tool that can support early intervention and personalized care [36].

Another study, this time a large, multicenter study by Kenney and his team of researchers, published in the journal Neurology in the same year, aimed to evaluate the diagnostic value of OCT in SD-OCT, combined with DL, for identifying anterior or MS-related optic neuritis.

The study was based on the analysis of data from over 2000 patients who were evaluated using a composite score developed by the research team, a score that includes both retinal thickness measurements and tests that assess visual function. With this model, an AUC of 0.89 was obtained, and therefore a strong diagnostic performance, intended to validate the use of OCT-based structural and functional biomarkers for the diagnosis of MS [35].

Montolío attempted to predict MS progression by using machine learning with OCT-derived biomarkers to improve both diagnosis and prognosis. In addition, they focused on RNFL and GCIPL. They showed that ML can effectively distinguish MS patients from controls and predict future problems, strengthening the clinical relevance of combining OCT with advanced analytics [37].

Other researchers proposed explainable AI in OCT analysis, recognizing that AI tools need to be transparent. Their study compared traditional black-box models with an explainable glass box approach (EBM), which used SHAP values to interpret model predictions and investigated the diagnostic importance of the temporal ganglion cell layer, where thinning was most indicative of MS [38].

Further advancing the technical precision of OCT imaging, Xie et al. (2022) developed a novel segmentation framework that combined a U-Net architecture with differentiable dynamic programming. This model excelled in delineating retinal layers even in images with weak boundaries, and demonstrated high segmentation accuracy on datasets from both age-related macular degeneration and MS patients, offering a robust solution for clinical image analysis [39].

Beyond imaging alone, Zhang et al. (2023) introduced a multimodal deep learning approach to assess MS disease severity. By combining electronic health records (EHR), neuroimaging, and clinical notes, their model significantly outperformed single-modality systems, achieving up to a 25% increase in classification accuracy. This integration highlights the value of holistic, data-rich AI models in personalizing MS care and improving outcome prediction [40].

Lastly, Schwab and Karlen (2020) explored the diagnostic potential of non-traditional data sources by applying deep learning to smartphone-derived digital biomarkers. Their model achieved an AUC of 0.88, showcasing the feasibility of using passive mobile data to support early and non-invasive MS detection. This innovative approach opens the door for broader, real-world monitoring of neurological health through everyday technology [41].

Together, these studies reflect the evolving landscape of AI in MS diagnostics, where deep learning, explainability, multimodal data integration, and accessible technologies are converging to redefine how the disease is identified and managed. OCT analysis based on artificial intelligence aims, in addition to increasing efficiency, to fundamentally change the way in which multiple sclerosis is diagnosed, monitored and managed in neurology clinics [42].

Multiple sclerosis is a disease with a clinical picture, sometimes extremely non-specific, which at first presentations can go unnoticed or minimized as symptoms, in the absence of a laborious imaging examination [43].

Using OCT and artificial intelligence, multidisciplinary teams based on neurologists and radiologists can establish the diagnosis of MS in a faster, more efficient and less expensive manner, since with the help of deep learning methods the time required for image interpretation can be significantly reduced [44].

With the help of these methods, even early signs of disease progression can be observed, signs that give retinal changes long before they give clinically evident symptoms. This early detection of changes allows clinicians to be one step ahead of the disease and to intervene in a timely manner to reduce long-term disability [45].

Another utility of artificial intelligence in detecting retinal changes detectable through OCT is the contribution to the creation of personalized treatment strategies by correctly and early identification of patients at high risk of worsening symptoms [46].

Table 2 provides an overview of the major longitudinal studies that have used ophthalmologic imaging methods in multiple sclerosis.

Table 2. Longitudinal Studies Using Ophthalmologic Imaging in MS.

Paper	Study Duration	Brief of Content	Results	Was Timeframe Suitable?
[27]	4 years	Longitudinal OCT tracking of RNFL and GCIPL loss	GCIPL loss preceded RNFL thinning, highlighting early biomarkers	Yes, allowed detection of temporal sequence of degeneration
[12]	2 years	Time-domain OCT in progressive MS	Showed gradual RNFL thinning	Partially, noted that longer follow-up may be needed for subtle changes
[17]	2 years	RNFL and brain volume analysis with cognitive correlation	RNFL thinning associated with cognitive scores	Yes, timeframe sufficient for multimodal analysis
[28]	2 years	RNFL changes and visual outcome correlation	RNFL thinning predicted worsening vision	Yes, structural changes correlated with disability progression
[29]	3 years	OCT/OCTA assessment of inner retina and choriocapillaris	Correlated retinal changes with EDSS	Yes, sufficient duration to detect progression in multiple layers
[30]	1 year	Comparison of treated vs untreated patients using OCT	Less RNFL thinning in treated group	Yes, therapeutic differences visible within a year
[31]	3 years	Longitudinal ERG + OCT in MS	Structural and functional decline observed	Yes, enabled parallel tracking of multiple measures
[32]	18 months	OCT and mfVEP to assess visual changes	Structural decline mirrored functional deterioration	Partially, hinted longer duration would improve confidence
[11]	12 months	SD-OCT analysis of INL and GCIPL	Detected microstructural changes without ON	Yes, changes were statistically significant at 1 year
[33]	2.3 years	OCT thickness vs. future disability in a large cohort	Retinal thinning predicted EDSS worsening	Yes, longitudinal outcomes strongly predicted disability risk

Automated OCT Analysis Key Techniques

In order for images obtained with OCT scans to be properly analyzed by AI models, they must first be preprocessed, which is an extremely important first step to eliminate artifacts and improve the clarity of the image itself [47].

To eliminate artifacts, background noise is initially removed so that there is no interference with accurate segmentation, followed by normalization to obtain standardized images in terms of intensity, allowing for consistency of

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analysis even when images from different OCT devices are analyzed. The final step is contrast enhancement to better see the layers of the retina so that AI models can detect even the most subtle structural changes [48].

After the preprocessing stage, the next step is retinal layer segmentation, which consists of accurately mapping and delimiting the component layers of the retina using AI models.

This step is of particular importance for the detection of multiple sclerosis lesions, as there are specific neurodegenerative changes of the pathology at the level of retinal layers, such as at the level of the retinal nerve fiber layer, the thinning of which reflects axonal loss, which can be an important marker of disease progression [49].

Another key layer of the retina, analyzable with the help of AI models in OCT images, is the inner plexiform layer of the ganglion cell, which is also one of the earliest to change during disease progression [15].

AI models also allow the calculation of the total macular volume, which allows the analysis of not only neurodegenerative but also inflammatory processes, another extremely important hallmark of multiple sclerosis [50].

There are several computational techniques that have been developed to offer a precise segmentation when it comes to OCT images of the retina.

The automatic segmentation stage has benefited greatly from the emergence of deep learning models, especially U-net, allowing artificial intelligence to see even the smallest changes in the retinal layers and therefore be extremely sensitive to even the most subtle signs of disease progression. After completing the segmentation process, AI models continue to extract information from the OCT images, such as the key biomarkers already mentioned, which provide important data on the severity of the disease and its progression. Calculation of the thickness of the retinal nerve fiber layer and the inner plexiform layer of the ganglion cell provides important information about the phenomenon of neurodegeneration by their thinning, while a decreased total macular volume from one assessment to another shows us new neuronal damage and disease progression. All these assessments are made automatically by deep learning models, which in addition to structural measurements can even identify abnormalities such as lesions or microcysts, which are important indicators of inflammatory activity in the retina [51].

Table 3 summarizes research using fundus photography and OCT AI-based data mining methods for MS diagnosis.

Table 3. AI-Based Data Mining in MS Diagnosis (Fundus/OCT).

Task	Model	Brief	Results	Paper
Segmentation	CNN with Eye-Tracking SS-OCT	Segmented retinal layers with high precision using swept-source OCT and CNNs	High accuracy in delineating inner retinal layers	[36]
Segmentation	Manufacturer AI Segmentation Tool	Automatic segmentation of Spectralis OCT scans	Enabled layer thickness quantification across visits	[37]
Segmentation	U-Net variant	Retinal boundary detection on SD-OCT	Robust to noise and structural irregularities	[52]
Classification	Neural Network + Cohen's d	Differentiated MS from controls using SS-OCT data	92% accuracy in early-stage diagnosis	[13]
Classification	CNN with Fundus Autoencoder (SLO-MSNet)	Applied to SLO images for MS subtype detection	88% accuracy, 91% specificity	[53]
Classification	Classic ML (SVM, RF)	Extracted features from retinal vessels and applied classifiers	Ensemble models performed best, >85% AUC	[54]
Classification	ML Classifiers on Pediatric OCT	Applied to OCT in children with MS	High sensitivity in detecting early changes	[55]
Prediction	Gradient Boosted Trees	Predicted EDSS progression using OCT + clinical data	OCT-derived GCIPL thinning predicted future disability	[37]
Prediction	Ensemble Learning	Used OCT and demographic data to forecast MS severity	Outperformed single-model approaches by >10%	[3]
Prediction	Explainable AI (SHAP + OCT metrics)	Identified key retinal biomarkers influencing prediction	Temporal GCIPL thinning most predictive	[56]
Prediction	Hybrid DL + Cognitive Assessment	Integrated OCT and neuropsychology to predict MS course	Significant boost in predicting cognitive decline	[37]

In addition to traditional machine learning models, support vector machines (SVM) and random forests also exist and have proven extremely useful, which are frequently used to classify these OCT-derived features, to provide clinicians with objective, data-driven assessments. In the meantime, more advanced deep learning models have also emerged, such as convolutional neural networks (CNN), which can completely skip the preprocessing stage and work directly with the raw images obtained by OCT [57].

Challenges and Future Directions

There are still countless challenges that remain in the way of integrating artificial intelligence on a large scale in the diagnosis and monitoring of multiple sclerosis using advanced retinal imaging [58].

Remarkable progress has been made in recent years, but there are still technical, ethical and practical issues that need to be resolved before the benefits of OCT and AI-enhanced imaging can be maximized [59].

The variability of imaging devices is one of the biggest challenges. Typically, images with different scanning protocols, resolutions, and formats are produced by different OCT and fundus camera manufacturers. As a result, deep learning models trained on the data may not perform consistently across devices [60].

This generalization issue underscores the importance of creating AI models that are able to adapt across platforms and standardized imaging protocols. To address this limitation and improve model robustness, it is essential to work together to build large, diverse, and multicenter datasets [61].

It is also worth mentioning the limited amount of annotated data. To create reliable AI models, a significant amount of labeled images is required, however, these datasets are rare, especially those focusing on MS, and annotating these images requires a lot of work and expertise, which leads to expense and time [62].

To accelerate progress and ensure reproducibility in future research, it is possible to build shared, open-access repositories of high-quality, expertly annotated OCT and fundus images [63].

Interpretability remains a significant issue, even as AI models improve. Many algorithms operate as “black boxes” and produce results without providing insight into the decision-making process. Lack of clarity is a major obstacle to clinical adoption, as for a tool to be successfully implemented, it must first be understood by the clinicians who will use it [64].

A number of new technologies, such as SHAP scores and Grad-CAM visualizations, offer a positive perspective on explainable artificial intelligence; however, more work needs to be done to strengthen model results and clinician confidence [65].

Ethical and regulatory considerations are important for shaping the future of AI in MS diagnosis. The use of patient imaging data raises complicated issues around data security, consent, and privacy. To meet the standards imposed by authorities such as the FDA and EMA, AI models must also undergo rigorous clinical validation. As AI moves closer to clinical implementation, it is more and more important to properly balance innovation with ethical responsibility [66].

Beyond the technical and regulatory aspects, there are real obstacles to implementing AI in routine clinical workflows. Many healthcare institutions may not have the resources or skilled personnel to effectively implement and manage AI systems. The user experience should be simple, easy, and compatible with existing healthcare systems when creating future AI tools. Interdisciplinary training and educational initiatives can also help facilitate easier adoption and collaboration between clinicians and technologists [67].

Integrating multimodal diagnostics is one of the most promising directions for AI in MS care.

A more complete picture of the disease can be obtained by combining fundus images with OCT MRI, patient history, and clinical test results. AI models that combine different types of information may be able to provide more accurate diagnoses, track the progression of a disability over time, and even predict future disease outcomes with greater accuracy. This transition toward personalized and predictive medicine is a natural evolution of current AI efforts [68].

Additionally, remote monitoring of MS is rapidly becoming possible as cloud-based analytics and portable retinal imaging devices become more widespread. Even from home, doctors can monitor patients in real time using inexpensive fundus cameras and smartphone-compatible OCT scanners. This progress would have multiple benefits for patients living in rural or disadvantaged areas, as it would allow them rapid access to specialized care and surgical interventions [69].

Integrative Discussion

A new era in the management of multiple sclerosis has been opened when artificial intelligence was integrated into retinal imaging, and this is due to the use of fundus imaging and OCT in combination with deep learning algorithms. This scoping review highlights how these AI-based techniques can improve

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diagnostic accuracy, track disease progression, and provide personalized treatment options, because AI has demonstrated the ability to outperform traditional manual approaches in terms of both speed and accuracy of imaging methods, from image preprocessing and retinal layer segmentation to advanced classification and prediction models [70,71].

The ability of deep learning models, especially CNNs, to extract complex structural patterns that may not be visible to the human eye is one of the most significant achievements in this field. These models have been able to identify important biomarkers such as RNFL thinning, GC-IPL degradation, and even macular volume changes, biomarkers that are linked to clinical scores of brain atrophy and disability [34,72].

Recent studies have shown that AI-driven analysis can be extended to fundus imaging, making neuro-ophthalmic diagnostics even more accessible [73].

The discovery of explainable AI techniques has been an important step in building clinicians' confidence to integrate these resources into the clinic. Importance maps, SHAP scores, and other interpretability mechanisms have helped clarify how and why certain predictions are made. These mechanisms are crucial for clinical decision-making and patient care. Recognition of multimodal diagnostic approaches, which combine OCT and fundus data with MRI, clinical records, and patient history, are equally important and will allow for the creation of a more complete and individualized model of MS assessment [45,74].

There are some [pissues that persist despite these advances such as device variability, lack of standardized data sets, limited data sharing, and regulatory and privacy concerns. In addition, the field needs larger clinical validation studies.

These studies should, in particular, evaluate the capacity of AI in different populations and real-world healthcare settings [69].

Costs, training, and infrastructure should also be considered before implementing AI in resource-limited setting, but the path to innovation in this area appears to be good. There is potential for the delivery of care to be revolutionized by wearable imaging technologies and cloud-based AI analytics platforms. The natural course of MS and the quality of life of patients worldwide can be improved through early diagnosis, continuous monitoring, and prompt intervention, all achieved with the help of non-invasive imaging and AI [75].

Conclusion

The diagnosis and treatment of complex diseases, such as multiple sclerosis, are being transformed by AI, which can identify subtle retinal changes through fundus imaging and OCT before clinical symptoms manifest.

Deep learning models enhance image interpretation, making it possible to classify MS subtypes, track disease progression, and evaluate disability more quickly, consistently, and objectively.

In terms of sensitivity, reliability, and variability, automated diagnosis outperforms human interpretation, particularly in conditions like multiple sclerosis.

Our findings suggest that, under the right conditions, fundus imaging may even outperform OCT in certain automated diagnostic tasks, especially when data availability or technical infrastructure is limited.

Conflict of interest

None to declare.

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