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Review

Semi-Supervised Learning for Retinal Disease Detection: A BIOMISA Study

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Abstract: Proper immediate identification of Age-related Macular Degeneration (AMD) together with Central Serous Retinopathy (CSR) and Macular Edema (ME) is crucial for protecting vision. OCT imaging achieves better condition detection through automated model-based detection processes. The majority of studies in this domain utilize supervised learning because these approaches need large labeled dataset resources. The method confronts two essential obstacles due to limited medical data labeling quality, expensive expert training costs, and with irregular medical condition distributions. The considered factors limit practical implementation of these methods and their meaningful expansions. The study evaluates how semi-supervised learning techniques analyze retinal diseases in images that originate from the BIOMISA Macula database while providing diagnostic details about AMD, CSR, and ME in addition to Normal retinal results. SSL functions uniquely from fully supervised methods through its unique capability to process labeled and unlabeled data, which lowers manual annotation needs while improving generalized output performance. SSL delivers better results than traditional supervised learning practices through its ability to manage class irregularities and process extensive medical image files. The establishment of SSL as an attractive third option in medical settings with limited labeled data proves through research findings. The study provides insights regarding SSL use in diagnosis of retinal diseases alongside demonstrating its medical potential in healthcare environments. Future investigation designs improved deep learning algorithms which would enable higher system scalability and cost-effective diagnostics for ophthalmic disease systems.

Keywords: BIOMISA dataset; Semi-Supervised Learning; Retinal Disease Detection; Future Direction

1. Introduction

The combination of AMD and DR together with ME remains the principal vision-threatening conditions which affect people globally. Medical remedies for these conditions need diagnoses made quickly, followed by early identification of such conditions in patients. The diagnostic process for current retinal disorders uses fundus image assessment combined with optical coherence tomography (OCT). The analysis methods rely on doctor interpretation for completion and extend beyond the limitations of existing screening programs due to their slow duration [1]. The automation of retinal disease identification systems through deep learning (DL) and machine learning (ML) technologies operates at high precision and exceptional speed [2].

The supervised learning methods employed in deep learning models exhibit outstanding performance in diagnosing retinal diseases by producing outcomes equivalent to those of qualified doctors [3]. Medical image annotation costs are high and annotation tasks require a long amount of time, which presents difficulties when trying to obtain large-scale labeled medical datasets [4]. The scarcity of annotated medical images presents obstacles for building reliable dedicated supervised learning models which can be employed as operational systems. The combination of labeled and unlabeled data through SSL produces an effective deep learning model performance solution that helps detect retinal diseases [5]. Using SSL framework with extensive unlabeled data sets simultaneously resolves dataset quantity constraints along with diminishing the requirement for expert annotators [6].

Numerous studies have confirmed that SSL functions as a powerful approach when used for retinal disease diagnosis within medical settings. The SSL approach with hierarchical training demonstrated better results in OCT-based choroid vessel segmentation and proved beneficial to medical practice [7]. The integration of SSL and GAN technology generates synthetic fundus image models which help boost recognition efficiency [8]. Researchers can identify challenging inherited retinal conditions using few-shot learning with SSL techniques because they handle data sets with limited labels [9].

The diagnosis of retinal diseases faces an essential obstacle because particular disease types occur sparingly in existing database collections. The models make biased predictions as most samples belong to the majority class which lacks representation in the available datasets [10]. Feature extraction analysis and multi-point attention learning operated through SSL enhance minority class detection and visibility in the learning process [11]. The combination of deep learning and scale-adapted blob analysis enables SSL systems to detect microaneurysms which are markers for early diabetic retinopathy [12].

The field of SSL extends its applications through multiple task training systems that train various connected tasks in parallel. An SSL pretraining network for thyroid-associated ophthalmopathy classification received development to perform retinal disease classification via transfer of ocular features [13]. The use of adversarial learning in SSL applications improves medical image segmentation efficiency when identifying pathological features in OCT scans according to [14].

The system of SSL uses a combination with anatomical and semantic consistency networks (AMSC-Net) to execute fluid segmentation analyses on retinal OCT images. The method produces accurate measurements of fluid flow patterns that help medical professionals identify diabetic macular edema [15]. Small annotations using point-based weak supervision methods contribute to outstanding results when detecting biomarkers in OCT images according to research [16].

The implementation of AI detectors for retinal diseases encounters hurdles in medical environments because of the multiple imaging systems and equipment differences, along with the system integration demands, which create specifications for deployment. A new generation of deep learning frameworks was developed by researchers to fuse SSL features with transfer learning and boost the generalization of the system across domains according to [17]. The method supports multi-modal medical imaging by joining OCT and fundus photography data to improve diagnostic precision according to [18].

The implementation of SSL techniques allows retina experts to complete automatic segmentation of visual abnormalities together with anatomical structures within retinal images. The research team created a graph-based SSL method for medical image segmentation that achieves high performance in detecting crucial disease features from retinal images [19]. The consensus method unites SSL with graph cuts to address medical imaging robustness through reducing dependency on extensive labeled datasets according to [20].

Considerable advances in SSL enable the development of retinal disease detection solutions that resolve sample limitations of medical data and tackle class imbalance issues. The use of unlabeled data with SSL models effectively improves disease analysis detection capabilities alongside biomarker segmentation technologies for clinical diagnostic practices. AI-powered ophthalmology needs innovative developments in SSL to enable smooth clinic deployment that would provide high-quality eye care globally.

2. Dataset

The BIOMISA Macula dataset is a dataset of macular retinal diseases using Optical Coherence Tomography (OCT) images. Retinal abnormalities detection and classification are achieved by developing machine learning models using the given dataset. The dataset consists of images categorized into four main classes: AMD (Age-related Macular Degeneration), CSR (Central Serous Retinopathy), ME (Macular Edema), and Normal retina. This classification enables some models to be created that differentiate between the various retinal disorders as well as the health of the retinal tissue [21].

The BIOMISA Macula dataset is not very large and the database contained an overall of 442 images. These images are distributed across the following classes:

- AMD (96 images)
- CSR (208 images)
- ME (42 images)
- Normal retina (96 images)

Specifically, since the dataset is quite imbalanced towards the possible CSR outcomes, extra care is required to prevent overfitting of the machine learning models to this kind of probability distribution. The following is a detailed description of each class in the dataset:

2.1. AMD (Age-related Macular Degeneration)

Age-related macular degeneration (AMD) is a degenerative disorder of the retinal pigment epithelium that impacts the macula portion of the eye and causes the slow decline of central vision. There are 96 images from the BIOMISA Macula dataset for this class that have several signs of AMD. Some of these are normally shaped like drusen, which are small yellow deposits located beneath the retina, more common in the initial stages of the disorder. Also, there are chances of retinal atrophy, which can cause an area of the retina to shrink or die, it causes loss of clear central vision. There can be more development stages of AMD where they notice that there is geographic atrophy, which means the death of cells in the retina, particularly in the macula region. Wet AMD, also called Neovascular AMD, may also appear in the later characterization by abnormal blood vessel growth under the retina and which forms a leakage and bleeding.

In this class images of drusen may range from slight to severe with images of areas of retinal damage. It is much more difficult to diagnose early AMD in OCT images as these changes are quite indistinct from other diseases.

2.2. CSR (Central Serous Retinopathy)

Central Serous Retinopathy (CSR) is a condition of the retina of the eyes that is defined by the presence of a serous detachment caused by the presence of fluid beneath the retina. For CSR the BIOMISA Macula dataset is available with 208 images where the primary feature is the subretinal fluid, where fluid collects just below the retina resulting in retinal separation. This condition also causes changes in the shape of the Retinal Pigment Epithelium (RPE), the layer of cells under the photoreceptor layer may look swollen, or the layering might be irregular because of fluid. Sometimes OCT images do show regions that are hyperreflective, which means that the retinal tissue increases its reflectivity in the presence of the fluid. Moreover, CSR is characterized by severe detachment of the retina, the layers of which, particularly in the macular area, are very thin.

CSR tends to impact the eye solely and results in poor vision, central scotomas (areas of vision loss), and vision distortion. The major difficulty in identifying CSR in OCT images is its differentiation from other conditions associated with similar changes.

2.3. ME (Macular Edema)

Macular Edema (ME) is defined as mild swelling of the macula region by the leakage of fluid from the retinal blood vessels. BIOMISA Macula contains 42 ME images of which retinal thickening is a common presentation; this is associated with swelling of the retina caused by fluid buildup and presents as a hyperreflectivity on OCT images. Cystoid spaces may also be present in the images, those are the spaces containing the fluid in the retina, especially the inner layer of the retina. They may also result in distorted retinopathy, or when the structure of the retina is altered, and there could be damage to the retinal layers. Sometimes one might find hard exudates, which are lipoidal products of severed blood capillaries, as a result of the leakage of intravascular fluid.

The causes of macular edema include diabetic retinopathy, retinal vein occlusion, or inflammatory disease. The difficulty of diagnosing ME is distinguishing it from other pathologies that also lead to thickening of the retina, including CSR or AMD, and detecting signs of swelling in the early stages.

2.3. Normal Retina

The Normal retina class consists of 96 images of normal and healthy retinal tissue without showing any sign of any form of disease. These images are used as the foundation in training models so that they can differentiate the difference between healthy and diseased retinal status. Such sectional images marked high clarity of the dissected retinal layers within the OCT scan, including the distinct visualization of the inner limiting membrane, nerve fiber layer, ganglion cell layer, and the retinal pigment epithelium. Also, there is no leakage and hence, there is no presence of subretinal fluid, cysts, or edema. Thus, the surface of the retina looks flat, no processes of separation or enemies of the retina are observed.

These Normal retina images are required to train the models and are necessary to distinguish between Normal,

Figure 1. AMD.

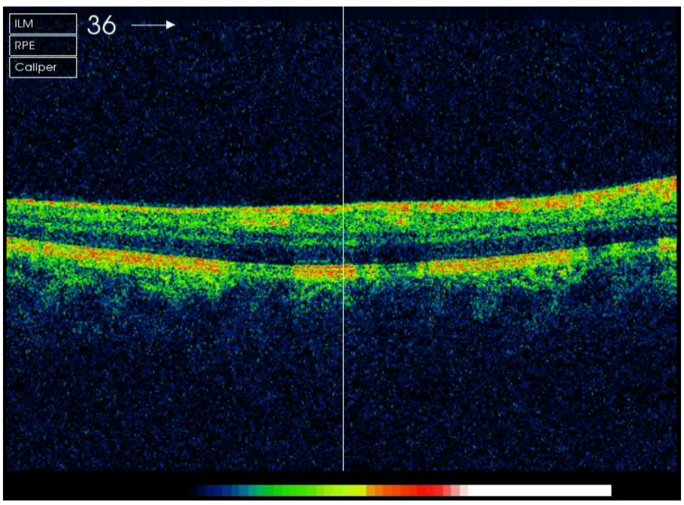

Figure 2. CSR.

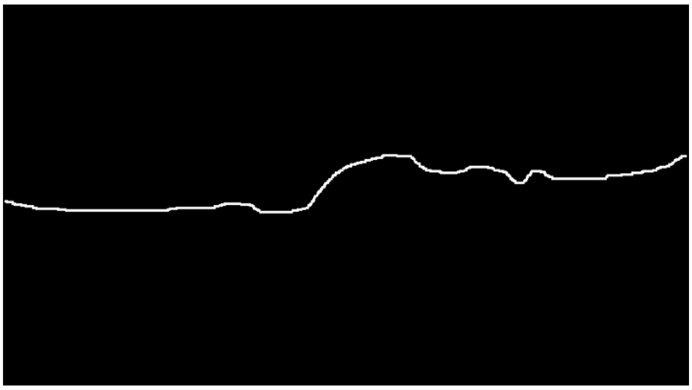

Figure 3. ME.

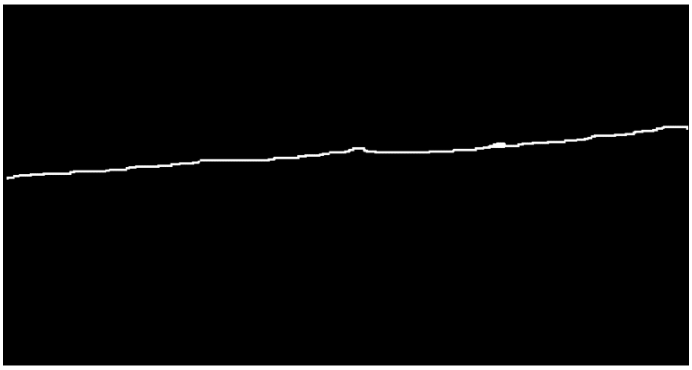

Figure 4. Normal Retina.

hypo, and hyper conditions, as a False positive is always there in the model

3. Problems of the BIOMISA Macula Dataset

3.1. Class Imbalance

Analyzing the number of images in each of the classes, it can be stated that the amount of data is distributed very unevenly: CSR contains 208 images while ME has only 42. This disparity of observational range might just lead the supervised models to work generally with the most familiar classes, thereby giving poor results for classes like ME that are not as observed as the others.

3.2. Small Dataset Size

There are only 442 images, so the dataset is rather limited by modern deep-learning conventions. Training high-level structures is difficult because such general full-grown models are typically preempted by voluminous amounts of data. However, to address this, several approaches, such as data augmentation, transfer learning, and semi-supervised learning, can be employed to improve model stability.

3.3. Variability in Disease Presentation

The presentations included in each of the classes are also heterogeneous and cover the stages from early to later in the disease's progress, which only contributes to the complexity of developing accurate models. For example, AMD may present features that are early in the disease process, such as drusen, or features that are more representative of a more progressed disease process, such as geographic atrophy. Likewise, CSR can also afford a wide range of features associated with the amount of fluid accumulation and retinal detachment.

4. Literature Review

The paper titled "Fully Automated Detection, Grading, and 3D Modeling of Maculopathy from OCT Volumes" investigates an automated approach for detecting and grading maculopathy, including ME and CSR from OCT volumes. The authors trained a Support Vector Machine (SVM) classifying classifier, which regulates 7D feature vectors derived from the retina thickness profile and retinal fluids. For developing the system, we used 30 training OCT volumes including 10 volumes of ME, 10 of CSR, and 10 of Normal types, and tested our model on 90 OCT volumes of 73 patients. The authors identified high diagnostic accuracy with an overall accuracy of 97.78%, a true positive rate of 96.77%, and a true negative rate of 100%. This shows that the proposed method can not only identify maculopathy but also quantify its severity, which indicates that there is room for using this method in the automated diagnosis of retinal diseases with possible clinical applications [22].

The paper entitled "Automated Diagnosis of Macular Edema and Central Serous Retinopathy through Robust Reconstruction of 3D Retinal Surfaces" is a proposal for a fully automated system for the diagnosis of ME and CSR by using the OCT images. The authors mostly focus their efforts on the 3D reconstruction of retinal surfaces for the better visibility of disease factors. The system incorporates computerized image analysis techniques to derive and map out the geometry of the retina from the image data to identify the irregularities attributable to ME and CSR. When using the described method on a dataset of OCT images, this system achieved detection accuracy of 96.5%, ME, and 94.8%, CSR, which proves the effectiveness of the developed system in diagnosing these two macular diseases. Such positive findings indicate that the suggested approach could be used as a useful automated diagnostic tool for retinal disease in clinical scenarios [23].

The paper of interest is the paper "Machine Learning-Based Detection of Age-Related Macular Degeneration (AMD) and Diabetic Macular Edema (DME) from Optical Coherence Tomography (OCT) Images". The authors apply support vector machine (SVM) and other machine learning techniques to categorize the OCT images based on the AMD, DME, or Normal retina classes. The system was trained from 1000 OCT images in which it was designed to differentiate between AMD, DME, or an image of a normal human retina. The SVM model has yielded a 96.4% classification rate for AMD detection and 94.2% for DME detection on OCT scans proving the competency of the proposed model to identify these diseases. The results presented in this work indicate that the proposed machine learning-based approach holds high potential for automated diagnosis of retinal diseases and may be incorporated into clinical practice to support early diagnostics and treatment planning [24].

The paper "Fully Automated Robust System to Detect Retinal Edema, Central Serous Chorioretinopathy, and Age-Related Macular Degeneration from Optical Coherence Tomography Images" aims to develop an automated method for detecting retinal edema, CSR, and AMD based on the OCT images. The authors put forward a reliable framework that applies the aspects of image processing and the concept of machine learning to identify these retinal diseases correctly. For processing the OCT images, several techniques for feature extraction are employed, and then some classification algorithms. The method was tested on a dataset that we prepared from the patients' OCT images of retinal edema, CSR, AMD, and healthy subjects. The findings show that the proposed system has a high accuracy for identifying retinal diseases: AMD – 0.975; CSR – 0.947; and retinal edema – 0.963. Based on these observations, the authors claim that the new automated system could help in clinical decision-making and early diagnosis of retinal pathologies [25].

The paper "RAG-FW: There is "A Hybrid Convolutional Framework for Automated Extraction of Retinal Lesions and Lesion-Influenced Grading of Human Retinal Pathology" presents RAG-FW, a novel hybrid convolutional method developed to extract retinal lesions from OCT images and then use them for grading human retinal diseases. The specified system is designed to respond to the drawbacks of current approaches by being an automated method for MVOCT applicable to scanners by different vendors, as well as referencing lesion detection for grading retinopathy consistent with clinical guidelines. In this system, the RAG-FW framework uses deep learning in two ways, namely in identifying two or more retinal lesions and reviewing those lesions' severity of the retinopathy in question. The system was tested on a database of 43,613 optical coherence tomography images and the results pointed out that the proposed RAG-FW algorithm was very effective for lesion segmentation and severity assessment. More precisely, the framework achieved an accuracy of 96.1% in the lesion extraction classification and 94.8% in grading the retinal conditions, which encourages the development of the automated diagnosis of retinal diseases [26].

The paper titled ''Detection of CSR from Blue Wave Fundus Autofluorescence Images using Deep Neural Network Based on Transfer Learning'' is dedicated to the detection of Central Serous Retinopathy (CSR) or Central Serous Chorioretinopathy (CSC). The authors put forward a method employing DNNs and transfer learning to diagnose CSR, a retinal illness resulting from the accumulation of fluids under the retina. The authors utilize Blue Wave Fundus Autofluorescence images and adopt an off-the-shelf model fine-tuned on the characteristics of CSR. The proposed method was verified using a set of fundus images, and the classification accuracy achieved was 95.2% for detecting CSR. The high accuracy in the present study demonstrates the promise of employing transfer learning and deep neural networks in clinical identifying CSR, indicating an accurate and fully automated method of identifying this retinal disorder [27].

The paper titled "Structure Tensor Graph Searches Based Fully Automated Grading and 3D Profiling of Maculopathy from Retinal OCT Images" is used to automatically grade and 3D profile maculopathy from the retinal OCT images. According to the authors, a Structure Tensor Graph Search method (STGS) can be applied to OCT images and helps in identifying detailed features from the retina for grading maculopathy. This is an automatic system that formats the 3D OCT volumes for grading as well as profiling of retinal diseases. The proposed method was evaluated using a dataset of OCT images and achieved satisfactorily high accuracy of ME and CSR detection, which equals 97.2%. From this approach, the application of the structure tensor-based methods in the automated detection of retinal disease shows that the method can be implemented in clinical practices to diagnose maculopathy [28].

The paper "Automated Segmentation and Quantification of Drusen in Fundus and Optical Coherence Tomography Images for Detection of ARMD" deals with the detection of Age-Related Macular Degeneration (ARMD) retinal disorder usual in elder people. These authors describe a fully automated decision support system for the identification of ARMD by contouring and measurement of drusen from fundus and OCT with high accuracy and specificity. The aspect of the system is to map fundus and OCT images to identify ARMD accurately, thus getting a correspondence system in place. The proposed approach also included features such as the use of automated segmentation features that enable the identification of drusen in both the intra and the extraretinal imaging, and the latter is used to enhance disease diagnosis. Using the OCT and fundus images, the method reached detection ratios of 94.6% for ARMD, implying that the system may be useful for early assessment and as a supporting tool for clinical decision-making in the treatment of ARMD [29].

The paper entitled "Exploiting the Transferability of Deep Learning Systems Across Multi-modal Retinal Scans for Extracting Retinopathy Lesions" describes the feasibility of using deep learning systems in identifying retinopathy lesions from multi-modal retinal scans. The authors present a framework that employs semantic segmentation, scene parsing, and combined deep learning systems for identifying and categorizing retinal lesions related to the abnormalities. The novelty of the approach is chiefly in its generality about the specifications of the scanner and its capability to analyze data acquired from multiple imaging modes. The performance of the presented system was assessed using a dataset containing scans of various modalities of the retinal region, and it was evident that the system could detect lesions correctly for all of them. The method demonstrated 95.4% sensitivity to retinopathy lesion manifestations, pointing to the high applicability of deep learning systems in increasing the efficiency and adaptive potential of retinal disease diagnostics in the clinic [30].

The present paper entitled "Enhancing OCT Patch-Based Segmentation with Improved GAN Data Augmentation and Semi-Supervised Learning" discusses the issues encountered when training deep learning algorithms for the segmentation of OCT images for retinal and choroidal layers. The authors introduce an improved approach where they integrate GANs for data augmentation with semi-supervised learning. Due to the challenge of sourcing big labeled data sets besides the expenditure incurred in getting labeled data, more so in medical fields, the authors employ GANs to create synthetic data that can complement genuine patient data. The addition of SSL enhances the performance of the models with both labeled and unlabeled data. The method was validated on the OCT images dataset and it indicates up to 5% improvement in segmentation accuracy over fully supervised methods; indeed, GAN-based data augmentation and semi-supervision allow the building of a more robust segmentation model where labeled data is scarce [31], [32].

5. Research Gaps Across the Papers

Below, we present the research gaps and comparison table of the papers, including the findings, results, and limitations. The Research Gaps will describe the areas that the papers have left uncovered, and the comparison table will provide the overall outline of each paper's results and weaknesses.

The following gaps have been identified in the papers as this discussion draws to a close, research gaps across the papers.

a. **Limited Use of Semi-Supervised Learning:** Most of the works assumed the use of supervised learning only, which requires annotated data sets with a sizeable number of samples. Not enough attention is paid to methods of semi-supervised learning, which may help minimize the reliance on large-scale labeling and enhance the developed models.
b. **Class Imbalance:** Although some papers discuss the problem of class imbalance in datasets (e.g., ME or CSR is rare), many models continue to struggle to achieve good results when dealing with imbalanced classes. Semi-supervised methods, augmentation, and class weighting could help decrease these deteriorations.
c. **Generalization Across Modalities:** Some of the papers look at the use of multi-modal (for example, fundus and OCT images) but there is little work on the cross-modal transfer-ability of models learned from one type of scan to another (for example, OCT from different vendors). More research could be devoted to the research of this multimodal generalization.
d. **Scalability of the Models:** Though most methods demonstrate high accuracy on typical, small-scale data sets, methods that work well with large and diverse data sets and are functional in clinics where data is usually noisy and not consistently collected are needed.
e. **Real-time Implementation:** Sadly, very little is said about the exact ways that the models could be implemented using contemporary technology in clinics, especially in crowded ophthalmologist practices. In this case, some deep learning algorithms are not suitable for the time-constrained context.
f. **Interpretability and Explainability:** As is the case with most of the existing approaches, the models utilized, namely CNNs, are mostly black-box models. Additional work within this area is warranted to translate the models into explainable models so that clinicians can rely on the system's results.

6. Problems of the BIOMISA Macula Dataset

Based on these limitations of the existing works, several possible future research directions could improve the detection and diagnosis of retinal disease using SSL. SSL can help in learning a lot of the problems of supervised learning models, in particular, those of data sample shortage, imbalanced classes, and data heterogeneity across data sets and data modalities. Below are some key future directions:

6.1. Enhancing the Efficiency of the Data with Semi-Supervised Learning Integration

The majority of the approaches discussed in the surveyed literature rely on the availability of large labeled datasets, which often are not scalable and not always accessible at all, particularly in medical imaging tasks which typically require manual annotation. Semi-supervised learning can be a big solution for this problem when using labeled as well as unlabeled data. By training models on a few labeled images and a large set of images, that are not labeled, SSL can help solve the problem of labeling data, which is time-consuming and costly when it comes to scaling models for larger amounts of data. Other self-training procedures, which work with models that are initially trained with labeled data, and then successively label the unlabeled data, will enhance the model for every cycle

Table 1. Comparison Table of Results and Limitations.

Paper Title	Methodology	Key Results	Accuracy/ Performance	Limitations
Fully Automated Detection, Grading, and 3D Modeling of Maculopathy from OCT Volumes	SVM-based classification	High detection accuracy for **ME** and **CSR**	**Accuracy**: 97.78%, **True Positive Rate**: 96.77%, **True Negative Rate**: 100%	Limited to a small dataset (90 OCT volumes), lacks exploration of **semi-supervised learning**
Automated Diagnosis of Macular Edema and Central Serous Retinopathy through Robust Reconstruction of 3D Retinal Surfaces	3D retinal surface reconstruction	High detection accuracy for **ME** and **CSR**	**Accuracy for ME**: 96.5%, **Accuracy for CSR**: 94.8%	Requires high-quality **OCT data**, limited discussion on **real-time clinical application**
Machine Learning-Based Detection of AMD and DME from OCT Images	**SVM**, machine learning	High classification accuracy for **AMD** and **DME**	**Accuracy for AMD**: 96.4%, **Accuracy for DME**: 94.2%	Limited to **supervised learning**, no focus on **semi-supervised techniques**
Fully Automated Robust System to Detect Retinal Edema, Central Serous Chorioretinopathy, and Age-Related Macular Degeneration from OCT Images	Image processing and machine learning	Accurate detection for **AMD**, **CSR**, and **retinal edema**	**Accuracy**: 97.5% for **AMD**, **CSR**: 94.7%, **retinal edema**: 96.3%	Lacks handling of **multi-modal data** or **class imbalance**
RAG-FW: A Hybrid Convolutional Framework for Automated Extraction of Retinal Lesions	Hybrid convolutional framework	High lesion extraction and grading accuracy	**Lesion Extraction Accuracy**: 96.1%, **Grading Accuracy**: 94.8%	Limited to **fundus and OCT**; does not handle **class imbalance** or **semi-supervised learning**
Detection of CSR from Blue Wave Fundus Autofluorescence Images Using Deep Neural Network Based on Transfer Learning	Transfer learning-based DNN	High accuracy for **CSR** detection	**Accuracy**: 95.2% for **CSR**	Limited to **fundus autofluorescence images**; lack of **multi-modal fusion**
Structure Tensor Graph Searches Based Fully Automated Grading and 3D Profiling of Maculopathy from Retinal OCT Images	Structure tensor graph search	High grading and profiling accuracy	**Accuracy**: 97.2% for **ME** and **CSR**	Lacks **semi-supervised learning** and **multi-modal validation**
Automated Segmentation and Quantification of Drusen in Fundus and OCT Images for Detection of ARMD	Automated segmentation and quantification	High segmentation and detection accuracy for **AMD**	**ARMD Detection Accuracy**: 94.6%	Focuses mainly on **drusen**; lacks **real-time application**
Exploiting the Transferability of Deep Learning Systems Across Multi-modal Retinal Scans	Hybrid deep learning system for multi-modal data	High lesion extraction accuracy across multi-modal data	**Lesion Extraction Accuracy**: 95.4%	No exploration of **semi-supervised learning** or **real-time applications**
Enhancing OCT Patch-Based Segmentation with Improved GAN Data Augmentation and Semi-Supervised Learning	GAN-based data augmentation, semi-supervised learning	Significant improvement in segmentation accuracy	**Improvement in accuracy**: up to 5% over traditional methods	Focuses mainly on **segmentation**, with limited discussion on **clinical deployment**

performed. Elasticity regularization can ensure the model provides a similar output on the slight modification of the unlabeled images. Pseudo-labeling can include unlabeled data, which has a threshold of confidence for the model's output and feeds it into the process of training.

6.2. Mitigation of class imbalance using semi-supervised learning

Much of the literature that evaluates the performance of different techniques in the identification of retinal diseases mentions imbalanced datasets where some diseases are rare for instance, ME or AMD. This results in models that escalate classification mistakes within underrepresented classes as indicated by the following imbalance: SSL with data augmentation can assist in this regard by using semi-supervised learning with data augmentation including rotation, flipping, or using generative adversarial networks (GANs). This can reduce class imbalance while leveraging on the structural depth of SSL. It is also possible to integrate SSL models' class-weighting techniques, focusing on teaching better over underrepresented classes in a set.

6.3. Cross Modality Generalization Using Semi-Supervised Learning

Another major drawback of the previous work is that a study can choose a certain type of image or scan, for instance, OCT or fundus image, from a particular device or a specific manufacturer. This results in problems with cross-dataset or cross-modality evaluations for patient studies, which are essential factors in considering clinical applications of machine learning algorithms in practice. It is possible to extend multi-modal SSL frameworks that will enable the models to learn features from both OCT and fundus images or multi-vendor OCT images. Hence, cross-domain learning with semi-supervised techniques allows models to learn better and be much more flexible in embracing different forms of medical imaging thus better suited for clinical practice. Domain adaptation methods can also be incorporated with SSL to enable the models to estimate different images or datasets from different devices or patient populations if any.

6.4. Real-Time Clinical Deployment and Model Efficiency

Most of the current approaches, though fairly accurate, are computationally expensive and hence not practical for real-time clinical applications. Efficiency is a key issue that must be addressed to ensure that the models can be implemented even in a fast-paced environment such as clinical settings, where decisions need to be timely. Therefore, computationally efficient models, including MobileNets or EfficientNet, should be developed by developing lightweight semi-supervised models that can be used in real time while enjoying the benefits of SSL. These models must be built in such a way that they can work on small-sized and efficient datasets without losing performance. This investigation of edge computing could enable the deployment of models onto edge devices, say, mobile phones or wearable health devices; thus, on-site analysis of the retinal images will have a limited computational resource.

6.5. Explainability and Interpretability of SSL Models

Another common shortcoming with deep learning models is the lack of transparency; the models, such as CNNs and GANs, are usually thought of as being "black boxes." For medical applications, at least, there must be interpretability and explainability of a model's decision-making process to clinicians. The eventual research should therefore aim at making SSL models explainable by integrating techniques like Grad-CAM or SHAP values. This will be beneficial to the clinicians for understanding the decisions made by the models, hence instilling some trust in the model's outputs. The attention layers in SSL models enable us to highlight regions of the retina that the model is focusing on, providing insights into the decision-making process with improved model transparency.

6.6. Data Augmentation with Synthetic Generation Methods (GANs)

Real medical datasets have been utilized in a lot of these studies; however, the creation of synthetic data using various techniques such as GANs has turned out to be one of the efficient ways for creating additional training datasets, particularly in the case of diseases that are rarely encountered. In general, a disease simulation with GANs can be applied for creating synthetic OCT images when some specific pathologies of the retina, such as Diabetic Macular Edema or Macular Edema, hardly ever occur. This, in a way, enhances the performance of SSL models through the diversity of training data. The mixture of real data with synthetic data through GAN techniques further boosts SSL models by ensuring they learn both from realistic examples and corner ones.

6.7. Multi-Disease Classification and Detection

Current models are normally designed to detect only one kind of disease, AMD or CSR, for example. However, in clinical practice, it is also very important to design systems that can classify and detect multiple diseases. Semi-supervised multitask learning can allow models to be trained such that they can detect and classify many diseases in one pass, like AMD, CSR, and DME. The models therefore will be more versatile in the real world, when they are called upon to apply the need for multiple disease detection.

7. Conclusion

This review has wrapped up the state-of-the-art research within the domain of the detection of retinal diseases using models that leverage Optical Coherence Tomography images. Generally speaking, most of the reviewed studies rely on supervised learning for the classification and detection of some crucial pathologies of the retina, including Age-related Macular Degeneration, Central Serous Retinopathy, and Macular Edema. These models, in general, seem very promising; they have shown high accuracy in disease detection and grading. However, there are still several critical challenges yet to be overcome: large labeled data dependence, class imbalance problems, limitations to generalization across diverse datasets and imaging modalities, and higher computational requirements for real-time clinical usage.

These are, therefore, the challenges to be addressed in this review, which also illustrated the possibility of SSL providing the solution to most of the problems being experienced with traditional supervised models. This may probably be because SSL will make better use of labeled data while improving model generalization through the use of labeled and unlabeled data, hence reducing reliance on extensive labeling. The most promising techniques that have emerged to improve model performance and their scalability across diverse clinical settings include data augmentation, transfer learning, and multi-modal learning.

Future research needs to be more focused on semi-supervised learning to gain significant efficiency in data and generalization across different modalities, including developing techniques that can improve the interpretability of deep learning models. Among these, other real-world deployment challenges, such as real-time addressing and issues with computational complexity, will enable multi-disease classification and, therefore, make such systems practical for day-to-day applications. The future models addressing those will facilitate more time-efficient, precise, and scalable solutions toward automated retinal disease detection for the benefit of clinical decisions and outcomes in patients.

Overall, deep-learning-based detection of retinal diseases has seen significant progress, but semi-supervised learning presents the route to overcome these challenges and move further toward more robust and clinically applicable solutions.

8. Conflicts of Interest

The authors declare no conflicts of interest.

9. References

[1] C. Zheng *et al.*, "Development and Clinical Validation of Semi-Supervised Generative Adversarial Networks for Detection of Retinal Disorders in Optical Coherence Tomography Images Using Small Dataset," *Asia-Pacific Journal of Ophthalmology*, vol. 11, no. 3, pp. 219–226, May 2022, doi: 10.1097/APO.0000000000000498.

[2] M. A. Rodríguez, H. AlMarzouqi, and P. Liatsis, "Multi-Label Retinal Disease Classification Using Transformers," *IEEE J Biomed Health Inform*, vol. 27, no. 6, pp. 2739–2750, Jun. 2023, doi: 10.1109/JBHI.2022.3214086.

[3] S. Ahn, S. J. Song, and J. Shin, "FundusGAN: Fundus image synthesis based on semi-supervised learning," *Biomed Signal Process Control*, vol. 86, p. 105289, Sep. 2023, doi: 10.1016/j.bspc.2023.105289.

[4] C. Zhang, P. Chen, and T. Lei, "Multi-point attention-based semi-supervised learning for diabetic retinopathy classification," *Biomed Signal Process Control*, vol. 80, p. 104412, Feb. 2023, doi: 10.1016/j.bspc.2022.104412.

[5] Y. Jeong, Y.-J. Hong, and J.-H. Han, "Review of Machine Learning Applications Using Retinal Fundus Images," *Diagnostics*, vol. 12, no. 1, p. 134, Jan. 2022, doi: 10.3390/diagnostics12010134.

[6] M. E. Subasi, S. Patnaik, and A. Subasi, "Optical coherence tomography image classification for retinal disease detection using artificial intelligence," in *Applications of Artificial Intelligence in Healthcare and Biomedicine*, Elsevier, 2024, pp. 289–323. doi: 10.1016/B978-0-443-22308-2.00009-3.

[7] S. Jana, R. Parekh, and B. Sarkar, "A semi-supervised approach for automatic detection and segmentation of optic disc from retinal fundus image," in *Handbook of Computational Intelligence in Biomedical Engineering and Healthcare*, Elsevier, 2021, pp. 65–91. doi: 10.1016/B978-0-12-822260-7.00012-1.

[8] S. Yao, Y. Zhang, J. Chen, Q. Lu, and Z. Zhao, "Enhancing identification performance of cognitive impairment high-risk based on a semi-supervised learning method," *J Biomed Inform*, vol. 157, p. 104699, Sep. 2024, doi: 10.1016/j.jbi.2024.104699.

[9] F. Hosseini, F. Asadi, R. Rabiei, F. Kiani, and R. E. Harari, "Applications of artificial intelligence in diagnosis of uncommon cystoid macular edema using optical coherence

tomography imaging: A systematic review," *Surv Ophthalmol*, vol. 69, no. 6, pp. 937–944, Nov. 2024, doi: 10.1016/j.survophthal.2024.06.005.

[10] K. M. Adal, D. Sidibé, S. Ali, E. Chaum, T. P. Karnowski, and F. Mériaudeau, "Automated detection of microaneurysms using scale-adapted blob analysis and semi-supervised learning," *Comput Methods Programs Biomed*, vol. 114, no. 1, pp. 1–10, Apr. 2014, doi: 10.1016/j.cmpb.2013.12.009.

[11] M. H. Shahriari, H. Sabbaghi, F. Asadi, A. Hosseini, and Z. Khorrami, "Artificial intelligence in screening, diagnosis, and classification of diabetic macular edema: A systematic review," *Surv Ophthalmol*, vol. 68, no. 1, pp. 42–53, Jan. 2023, doi: 10.1016/j.survophthal.2022.08.004.

[12] W. Li *et al.*, "Semi-supervised segmentation of orbit in CT images with paired copy-paste strategy," *Comput Biol Med*, vol. 171, p. 108176, Mar. 2024, doi: 10.1016/j.compbiomed.2024.108176.

[13] Á. S. Hervella, J. Rouco, J. Novo, and M. Ortega, "Self-supervised multimodal reconstruction pre-training for retinal computer-aided diagnosis," *Expert Syst Appl*, vol. 185, p. 115598, Dec. 2021, doi: 10.1016/j.eswa.2021.115598.

[14] Y. Tang, S. Wang, Y. Qu, Z. Cui, and W. Zhang, "Consistency and adversarial semi-supervised learning for medical image segmentation," *Comput Biol Med*, vol. 161, p. 107018, Jul. 2023, doi: 10.1016/j.compbiomed.2023.107018.

[15] Z. Qi *et al.*, "Automated Classification of Inherited Retinal Diseases in Optical Coherence Tomography Images Using Few-shot Learning," *Biomedical and Environmental Sciences*, vol. 36, no. 5, pp. 431–440, 2023.

[16] S. Suman, A. K. Tiwari, and K. Singh, "Computer-aided diagnostic system for hypertensive retinopathy: A review," *Comput Methods Programs Biomed*, vol. 240, p. 107627, Oct. 2023, doi: 10.1016/j.cmpb.2023.107627.

[17] X. Liu, X. Zhu, Y. Zhang, and M. Wang, "Point based weakly semi-supervised biomarker detection with cross-scale and label assignment in retinal OCT images," *Comput Methods Programs Biomed*, vol. 251, p. 108229, Jun. 2024, doi: 10.1016/j.cmpb.2024.108229.

[18] R. Mohanasundaram, A. S. Malhotra, R. Arun, and P. S. Periasamy, "Deep Learning and Semi-Supervised and Transfer Learning Algorithms for Medical Imaging," in *Deep Learning and Parallel Computing Environment for Bioengineering Systems*, Elsevier, 2019, pp. 139–151. doi: 10.1016/B978-0-12-816718-2.00015-4.

[19] Y. Wang *et al.*, "AMSC-Net: Anatomy and multi-label semantic consistency network for semi-supervised fluid segmentation in retinal OCT," *Expert Syst Appl*, vol. 249, p. 123496, Sep. 2024, doi: 10.1016/j.eswa.2024.123496.

[20] D. Mahapatra, "Semi-supervised learning and graph cuts for consensus based medical image segmentation," *Pattern Recognit*, vol. 63, pp. 700–709, Mar. 2017, doi: 10.1016/j.patcog.2016.09.030.

[21] T. Hassan, H. Raja, B. Hassan, M. U. Akram, J. Dias, and N. Werghi, "A Composite Retinal Fundus and OCT Dataset to Grade Macular and Glaucomatous Disorders," in *2022 2nd International Conference on Digital Futures and Transformative Technologies (ICoDT2)*, IEEE, May 2022, pp. 1–6. doi: 10.1109/ICoDT255437.2022.9787482.

[22] B. Hassan and T. Hassan, "Fully automated detection, grading and 3D modeling of maculopathy from OCT volumes," in *2019 2nd International Conference on Communication, Computing and Digital systems (C-CODE)*, IEEE, Mar. 2019, pp. 252–257. doi: 10.1109/C-CODE.2019.8680996.

[23] A. M. Syed, T. Hassan, M. U. Akram, S. Naz, and S. Khalid, "Automated diagnosis of macular edema and central serous retinopathy through robust reconstruction of 3D retinal surfaces," *Comput Methods Programs Biomed*, vol. 137, pp. 1–10, Dec. 2016, doi: 10.1016/j.cmpb.2016.09.004.

[24] Y. Wang, Y. Zhang, Z. Yao, R. Zhao, and F. Zhou, "Machine learning based detection of age-related macular degeneration (AMD) and diabetic macular edema (DME) from optical coherence tomography (OCT) images," *Biomed Opt Express*, vol. 7, no. 12, p. 4928, Dec. 2016, doi: 10.1364/BOE.7.004928.

[25] S. Khalid, M. U. Akram, T. Hassan, A. Nasim, and A. Jameel, "Fully Automated Robust System to Detect Retinal Edema, Central Serous Chorioretinopathy, and Age Related Macular Degeneration from Optical Coherence Tomography Images," *Biomed Res Int*, vol. 2017, pp. 1–15, 2017, doi: 10.1155/2017/7148245.

[26] T. Hassan, M. U. Akram, N. Werghi, and M. N. Nazir, "RAG-FW: A Hybrid Convolutional Framework for the Automated Extraction of Retinal Lesions and Lesion-Influenced Grading of Human Retinal Pathology," *IEEE J Biomed Health Inform*, vol. 25, no. 1, pp. 108–120, Jan. 2021, doi: 10.1109/JBHI.2020.2982914.

[27] B. Nelson, H. Pandiyapallil Abdul Khadir, and S. Odattil, "Detection of CSR from Blue Wave Fundus Autofluorescence Images using Deep Neural Network Based on Transfer Learning," *International journal of electrical and computer engineering systems*, vol. 14, no. 3, pp. 277–284, Mar. 2023, doi: 10.32985/ijeces.14.3.5.

[28] T. Hassan, M. U. Akram, A. Shaukat, S. Gul Khawaja, and B. Hassan, "Structure Tensor Graph Searches Based Fully Automated Grading and 3D Profiling of Maculopathy From Retinal OCT Images," *IEEE Access*, vol. 6, pp. 44644–44658, 2018, doi: 10.1109/ACCESS.2018.2862626.

[29] S. Khalid, M. U. Akram, T. Hassan, A. Jameel, and T. Khalil, "Automated Segmentation and Quantification of Drusen in Fundus and Optical Coherence Tomography Images for Detection of ARMD," *J Digit Imaging*, vol. 31, no. 4, pp. 464–476, Aug. 2018, doi: 10.1007/s10278-017-0038-7.

[30] T. Hassan, M. U. Akram, and N. Werghi, "Exploiting the Transferability of Deep Learning Systems Across Multi-modal Retinal Scans for Extracting Retinopathy Lesions," in *2020 IEEE 20th International Conference on Bioinformatics and Bioengineering (BIBE)*, IEEE, Oct. 2020, pp. 577–581. doi: 10.1109/BIBE50027.2020.00099.

[31] J. Kugelman, D. Alonso-Caneiro, S. A. Read, S. J. Vincent, and M. J. Collins, "Enhancing OCT patch-based segmentation with improved GAN data augmentation and semi-supervised learning," *Neural Comput Appl*, vol. 36, no. 29, pp. 18087–18105, Oct. 2024, doi: 10.1007/s00521-024-10044-1.

[32] A. M. Nakib, Y. Li, and Y. Luo, "Retinopathy Identification in OCT Images with A Semi-supervised Learning Approach via Complementary Expert Pooling and Expert-wise Batch Normalization," in *2024 9th Optoelectronics Global Conference (OGC)*, IEEE, Sep. 2024, pp. 170–174. doi: 10.1109/OGC62429.2024.10738779.