AI and Explainable AI for Automatic Detection and Grading of Diabetic Retinopathy and Related Ophthalmic Diseases: A Review

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Abstract- The management of retinal diseases within a national health service is greatly improved by the availability and development of good automatic systems for eye disease identification and grading. Identifying the characteristics of retinal diseases, particularly diabetic retinopathy, is a challenging and lengthy process. Artificial intelligence (AI) and explainable AI (XAI) are reshaping the landscape of automated ophthalmic diagnostics, with diabetic retinopathy (DR) emerging as a central benchmark for such innovations. This review paper offers a thorough and critical examination of AI and XAI methodologies in this domain, with DR as the primary core focus area. Artificial intelligence, and especially deep learning, now facilitates precise and swift identification of retinal lesions and disease classification, while explainable AI enhances interpretability, transparency, and clinical confidence. This review paper synthesizes recent AI and XAI developments for DR and other ophthalmic diseases, covering image pre-processing, deep learning architectures and feature extraction as well. In order to contextualize the discussion, relevant background information on diabetic retinopathy and related retinal diseases is presented, including a detailed overview of the characteristic pathological features and the screening procedures commonly adopted by healthcare services. Furthermore, this article examines the publicly available eye fundus image datasets that serve as valuable resources for research in this domain. In view of the inherent challenges in developing automated screening systems, the paper concludes with a critical evaluation of current limitations and an exploration of prospective directions for future developments on AI and XAI for diabetic retinopathy and other ophthalmic diseases.

Keywords: Artificial intelligence, explainable ai, diabetic retinopathy, ophthalmic disease detection, retinal fundus imaging.

1. Introduction

There is a primary focus in health services today on preventive and interventional strategies on ocular ailments, which include a diverse range of issues that affect the visual system and result in vision impairment or even blindness. Cataract, age-related macular degeneration, trachoma, diabetic retinopathy, corneal opacity, glaucoma, and refractive error are all primary causes [1]. Diabetes can cause a number of visual disorders, including alterations in vision, double vision, cataracts, diabetic retinopathy, and glaucoma. Diabetic retinopathy is the only illness that diabetes directly causes, and it is the typical reason of sight loss in those with the disease [2].

Diabetic retinopathy is a gradual eye condition that injuries the tiny blood vessels in the retina, and is one of the most common complications of long-term diabetes. It affects a lot of people with diabetes, and if it is not treated, it can cause permanent eyesight loss. After some time, the little retinal vessels get destroyed, which makes the problem worse and makes it harder for a person to see.

The eleven edition of the International Diabetes Federation Diabetes Atlas [3] presents detailed worldwide, regional, and national estimations of diabetes for 2024 and predictions up to 2050. It highlights the growing worldwide impact of diabetes and calls for urgent, evidence-based action from governments and policymakers to address this main public health issue. According to the report, diabetes continues to be one of the grow rapidly health challenges of the 21st century. Around 589 million adults aged 20 to 79 were living with diabetes in 2024, along with more than 9.5 million people affected by type 1 diabetes, including about 1.9 million children and adolescents under 20. By 2050, this number is expected to rise sharply to 853 million people worldwide [3].

2019 research from the World Health Organization [1] said that beyond 2.2 billion individuals around the world have some kind of vision problem, and at least 1 billion of those instances might have been avoided or cured. The worldwide eye care sector is having a lot of trouble. For example, not everyone has equitable access to good prevention and treatment, there are not enough trained eye care workers, and eye care is not well integrated into other health systems. The World Report on Vision [1] wants to deal with these problems and get people all across the world to work together to make everyone's eye health better.

The Diabetic Retinopathy Barometer [4] is a large international study involving nearly 7,000 individuals with diabetes and healthcare professionals from 41 countries. Its findings underline the urgent need for clearly defined patient care pathways and strong, flexible healthcare systems worldwide to help prevent avoidable vision loss caused by diabetes.

The International Diabetes Federation, in partnership with the Fred Hollows Foundation, established the International Council of Ophthalmology Guidelines for Diabetic Eye Care [2]. In addition to fostering integration and collaboration across all levels of the health system, it also promotes effective management of diabetes mellitus, timely identification, and appropriate diabetic eye diseases treatment.

A short policy [5] developed by the International Agency for the Prevention of Blindness and the International Diabetes Federation provides support to manage and prevent visual disorders in people with diabetes mellitus, by including diabetic retinopathy care into national health plans and diabetes policies.

The American Diabetes Association's (ADA) 2023 Annual Report [6] highlights substantial progress in research, education, advocacy, and community support. It funded 171 research initiatives, updated its Standards of Care, and improved professional training through the newly formed Institute of Learning. The ADA aimed to improve the affordability and accessibility of insulin and diabetes technology. Community efforts like ADA Camps and Project Power have facilitated several individuals in attaining healthier lifestyles. Through strong partnerships and remarkable fundraising efforts, which raised nearly $144.7 million, the ADA has been able to advance its mission of improving health for everyone affected by diabetes.

Regular diabetic retinopathy screening is very important for first finding the disease and then starting treatment right away. Accurate retinal screening and proper interpretation of retinal pictures are essential for guaranteeing a dependable diagnosis. A well-designed clinical screening system could make it much easier to find and treat diabetic retinopathy. Automated tools could help doctors find the illness in its early, most treatable phases.

Support vector machines (SVM), random forests, and k-nearest neighbors (k-NN) are just some examples of Artificial Intelligence (AI) techniques that were used to classify eye fundus images in the past. Even though these techniques were rather straightforward and easy to use and understand, it was often challenging to get the full complexity of retinal images. Deep learning, and especially convolutional neural networks (CNNs), have made a huge difference. CNNs let computers learn important patterns from images on their own, which leads to more accurate classification results. However, deep learning models depend on large, well-labeled datasets and can be hard to understand. To overcome these difficulties, researchers are using different AI algorithms together to get the most out of each individual method. The goal is to make AI systems that work well and are also easy to understand, are reliable, and useful for doctors and patients to use in real-life situations.

AI is becoming a big part of modern medicine, especially when it comes to finding eye diseases like diabetic retinopathy. AI models, when trained well, can often be just as accurate as doctors who have been practicing for a long time, and they can produce reliable results and faster. But we can only trust them so much based on the quality of the data they were trained on and how effectively they work in real life. A lot of AI models are still "black box" models, which means it is hard to tell how they make their decisions. This can make doctors less likely to trust them. Explainable AI (XAI) helps change that by making AI judgements easy to explain, which builds trust and enables doctors employ AI securely in their daily work.

This paper offers a thorough and insightful review of how artificial intelligence (AI) and explainable AI (XAI) are being utilized to diagnose retinal diseases, focusing primarily on diabetic retinopathy (DR). It surveys DR screening comprehensively, including epidemiological trends, screening procedures, and the open-access databases that inform current research. Along with an assessment of image manipulation pipelines, extraction of feature approaches, and machine learning techniques for automated DR detection, the review identifies long-standing limitations in both screening and diagnosis, as well as opportunities for innovation and enhanced practical application. The main contribution of this paper is summarizing recent advances in AI and XAI techniques in this application, evaluating their advantages and limitations.

The structure of this paper is as follows. Some fundamental knowledge on diabetic retinopathy, including its incidence and the distinguishing features of each DR stage, together with a detailed overview of related eye diseases and the screening process of diabetic retinopathy are presented in Section 2. Section 3 outlines the publicly available databases commonly used in the research on diabetic retinopathy. The employed image processing techniques in the diabetic retinopathy detection and other related disease, including diabetic retinopathy classification, pathological feature and maculopathy detection are explained in Section 4. The diabetic retinopathy pre-processing techniques and related retinal diseases, the feature extraction methods utilized for detection purposes and the machine learning methods, including deep learning methods, applied in the diabetic retinopathy classification and related diseases are also described in Section 4. Section 5 emphasizes on the implementation of explainable artificial intelligence (XAI) approaches employed for eye fundus image processing. Section 6 wraps up the paper with some concluding remarks and a discussion of current screening practices and automated detection systems. Section 7 then looks ahead, outlining potential directions for future research and development.

1.1 Search Strategy and Study Selection

A systematic search was conducted via PubMed, Scopus, Web of Science, and IEEE Xplore to deliver a complete overview of AI and XAI applications in retinal disease diagnosis. The studies that were looked at in this review were published between 2010 and 2025. To find the most relevant research papers, we searched using keywords such as "artificial intelligence", "explainable AI", "diabetic retinopathy", "ophthalmic disease detection", "retinal fundus imaging", and "deep learning" to identify the most pertinent studies.

We focused on studies that used AI, and especially XAI (on which there is currently no review paper in this application) to detect or classify retinal diseases, excluding those that were unclear, with missing data, or not directly relevant. After removing duplicates, we screened titles and abstracts and then carefully went through the remaining papers, paying close attention to the methods, datasets, and results. This approach provided a clear and reliable picture of the latest advances in using AI and XAI to help diagnose eye diseases.

2. Ophthalmic Diseases and Eye Fundus Screening

This section looks at how diabetic retinopathy and other eye conditions can impact vision, highlighting why they matter clinically and the complications they can cause. It also emphasizes the value of early detection through eye fundus screening and review the strategies currently used to support accurate diagnosis and effective care.

2.1. Diabetic Retinopathy

Diabetic retinopathy (DR) is a lengthy, progressive illness that influence the small retinal vessels of the eye. It happens when patients with diabetes have high blood glucose levels during long periods of time. Injury to these capillaries, via weakening or obstruction, results in a range of retinal alterations collectively termed diabetic retinopathy. As a serious diabetes complication, DR can cause visual impairment and, in severe cases, blindness. Vision loss typically occurs via two principal mechanisms: the proliferation of abnormal retinal blood vessels, which may result in haemorrhages and retinal detachment (i.e., proliferative retinopathy); and localized vascular leakage causing oedema and swelling in the macula, thereby compromising central vision (i.e., maculopathy) [5].

Moreover, vision impairment resulting from diabetic retinopathy can severely impede efficient diabetes management, as numerous critical self-care activities such as preparing insulin injections and monitoring blood glucose levels, are heavily reliant on visual acuity. This impairment may lead to inadequate glycaemic management, heightening the risk of further diabetes-related problems. The consequent pressure extends beyond the individual, leading to increased healthcare costs and broader societal consequences [5].

The DR Barometer Global Report [5] shows that there are big holes in the way diabetic eye disease is managed around the world. Eighteen percent of patients reported that long wait times for appointments prevented them from getting eye exams, while 27% said they either never discussed eye problems with their doctors or only did so after symptoms appeared. On the provider side, 44% of healthcare professionals had no written protocols, or did not use them for managing diabetes-related vision loss, and 21% of healthcare professionals had insufficient training in diagnosing or treating diabetic retinopathy or diabetic macular oedema. The impact on daily life is significant, 79% of people with diabetic retinopathy or diabetic macular oedema said they struggled with everyday activities like driving, working, or household chores, and some reported being unable to do these things at all. Also, 20% said that their eye impairment made it harder for them to take care of their diabetes on their own, and 69% of those with diabetic macular oedema said they had times when their physical or mental health was bad.

Among first visible diabetic retinopathy (DR) signs are the dilation of retinal veins and development of microaneurysms - small swellings in the walls of capillaries brought on by vascular occlusion. Usually asymptomatic and not vision affecting, this first phase is called as the nominal non-proliferative diabetic retinopathy (NPDR). When the illness becomes more severe, vascular leakage and occlusion cause tiny haemorrhages and other retinal changes, so advancing DR from minimal to mild non-proliferative diabetic retinopathy. By this time, features including nerve fibre layer infarcts, retinal haemorrhages, and hard exudates become clear. Capillary growth and retinal venous beading define the moderate NPDR. Abnormal retinal vessel development, called neovascularisation, points to the so-called progressive proliferative diabetic retinopathy (PDR). The scenario significantly increases the likelihood of blindness and acute vision loss. These actions are illustrated in Figure 1. Figure 1 shows variations between a healthy retina and one with DR characteristics including cotton wool spots, microaneurysms, haemorrhages and exudates.

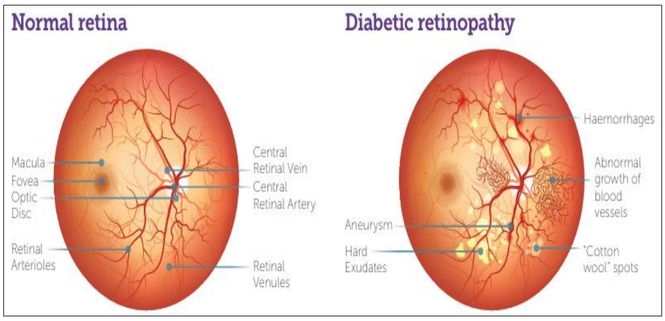

Fig. 1. Healthy retina vs. unhealthy retina visualisation [2].

2.2. Related Eye Diseases

Vascular mechanisms, which involve microvascular and macrovascular pathways, and nonvascular factors, are both responsible for the development of diabetic complications. Serious consequences, including lower-limb amputations, chronic kidney disease, and vision loss, are frequently the result of microvascular disease, including diabetic nephropathy, neuropathy, and retinopathy [7]. Complications of macrovascular, including peripheral vascular disease, cardiovascular disease, and cerebrovascular disease, are not exclusive to diabetes; however, they are substantially more prevalent among those who are affected. These macrovascular conditions collectively establish a high-risk triad that significantly contributes to increased morbidity and mortality rate.

The IDF Diabetes Atlas indicates that Diabetic Eye Disease (DED) typically arises from prolonged hyperglycemia, which damages the retinal capillaries, resulting in capillary leakage and blockage. If overlooked, this condition may lead to progressive visual impairment and ultimately blindness. The spectrum of diabetic eye disease includes cataracts, glaucoma, diabetic retinopathy, reduced concentrating ability, diabetic macular oedema, and diplopia, all of which can significantly compromise ocular health and visual function [8].

Diabetes is linked to a range of ocular disorders, such as refractive alterations, diplopia, diabetic retinopathy, cataracts, and glaucoma [5]. Diabetic retinopathy is distinct in its direct causation by diabetes and is the principal reason of visual problems. Although the other illnesses are not directly caused by diabetes, they manifest more frequently and, in certain instances, advance more swiftly in diabetes affected persons.

Diabetic retinopathy is the most mutual microvascular complication, but diabetic eye disease is not limited to it. Henriques et al. [9] added that diabetes mellitus can also lead to other ocular disorders, including blepharitis, chalazion, dry eye syndrome, corneal ulcers and neurotrophic keratitis. These conditions can significantly compromise visual function and increase the risk of progressive ocular damage.

2.3. Diabetic Retinopathy Screening

The International Agency for the Prevention of Blindness and The International Diabetes Federation jointly advocate for the integration of diabetic retinopathy attention into domestic diabetes health strategies and policies through cross-sector collaboration. Their recommendations emphasize strengthening diabetes care at all levels, implementing context-sensitive diabetic retinopathy screening and treatment interventions, and ensuring universal health coverage for services that reduce the risk of vision impairment. They also want solid population-level data to be collected, national systems to be reinforced to track disease trends, and diabetic retinopathy to be included in global diabetes targets [5]. At the heart of these initiatives is a focus on people-centered care and a global research agenda that pushes for new ideas in health care and makes sure that research results are used.

It can be quite stressful and disturbing to live with diabetic retinopathy that could cause you to lose your sight. Because treatments are personalized and responses vary, it is often unclear how long care will take or what the ultimate impact on vision will be. This uncertainty can make day-to-day life even more difficult, especially for those trying to balance work, family, or caring for others while keeping up with ongoing medical appointments [5].

To reach more people, diabetic retinopathy screening should be part of routine diabetes care. Technological advances in digital retinal photography now enable effective screening without the need for on-site eye specialists. Retinal images can be reviewed by trained technician, even those without formal eye health training or assessed remotely through teleophthalmology [5]. Recent breakthroughs in artificial intelligence (AI) have demonstrated considerable potential in assisting non-experts with accurate assessment of diabetic retinopathy severity. Patients diagnosed with moderate to severe diabetic retinopathy must be swiftly sent to professional ophthalmology facilities for further assessment and treatment. Effective collaboration between diabetes and ophthalmology services is crucial for patients to navigate the treatment route efficiently and receive timely treatments.

Multiple screening procedures are available for diabetic retinopathy, including direct ophthalmoscopy, eye fundus photography, indirect ophthalmoscopy, and slit-lamp biomicroscopy. Different screening methodologies will yield varying sensitivity and specificity ratings. Currently, all registered diabetes patients often have a visual acuity (VA) assessment first. Then, visual acuity is assessed after color fundus photography using an eye fundus camera. Trained paramedics will classify the collected eye fundus photos into diabetic retinopathy categories based on the discovered anomalies in the photographs. The patient's severity will be determined according to the recognized stage of retinopathy, which may include a follow-up management or an ophthalmologist referral for additional assessment.

The Malaysian Ministry of Health (MOH) is exploring how artificial intelligence (AI) can improve early screening for cancer, tuberculosis, and diabetic retinopathy [10]. Various test runs led by the Malaysian Health Assessment Section (MaHTAS) are already showing that AI can boost detection accuracy and help doctors make better decisions, especially when staffing is limited. Key initiatives include AI-assisted lung cancer screening, imaging for breast and cervical cancers, and for DR.

As reported by the Diabetic Retinopathy Preferred Practice Pattern in 2020 [11], the global rise in diabetes prevalence is leading to an increased diabetic retinopathy and sight-threatening diabetic retinopathy incidence. Currently, around 60% of individuals with diabetes receive the advised annual testing for diabetic retinopathy. Individuals diagnosed with type 1 diabetes should commence annual screenings five years following the diagnosis, while those with type 2 diabetes require immediate screening upon diagnosis and at least annual evaluations thereafter. Rigorous regulation of glycaemic levels and blood pressure is essential in averting the initiation and advancement of diabetic retinopathy, and patients should be advised accordingly. Pregnant women with pre-existing diabetes must receive early and regular eye tests, although this is not required for gestational diabetes. Adolescents with diabetes exhibit accelerated diabetic retinopathy progression during puberty and require more vigilant care.

The 2024 Diabetic Retinopathy Preferred Practice Pattern [12] revealed that, despite established criteria, only approximately 60% of individuals with diabetes mellitus undergo annual screenings for diabetic retinopathy. While the dilated fundus examination is the definitive standard, validated digital imaging is a feasible alternative for detection.

3. Retinal Image Databases

Many publicly accessible datasets with eye fundus photographs are available and facilitate the studies on diabetic retinopathy identification. Among the most often used in are the Digital Retinal Images for Vessel Extraction (DRIVE), the Standard Diabetic Retinopathy Database Calibration Level 0 (DIARETDB0), Methods to Evaluate Segmentation and Indexing Techniques in the Field of Retinal Ophthalmology (MESSIDOR), the Standard Diabetic Retinopathy Database Calibration Level 1 (DIARETDB1), the Retinopathy Online Challenge (ROC), the Indian Diabetic Retinopathy Image Dataset (IDRiD), Structured Analysis of the Retina (STARE), the Retinal Vessel Image Set for Estimation of Widths (REVIEW), the UHB Eye Image Dataset Release 001, the TJDR Dataset, the Mobile Brazilian Retinal Dataset (mBRSET) and the Diabetic Retinopathy Detection dataset from Kaggle. Some dataset like DRIVE, STARE, MESSIDOR, DIARETDB0, REVIEW, ROC and DIARETDB1 are old datasets, they are described below for historical purposes and because they are still used today as a benchmark due to providing good ground truths.

Comprising both normal and diabetic retinopathy eye fundus photographs, the Standard Diabetic Retinopathy Database Calibration Level 0 (DIARETDB0) is among the earliest publicly available datasets [13]. Of the 130 photos total, 20 are deemed normal (showing no indications of diabetic retinopathy); the other 110 reveal various pathological characteristics including soft exudates, haemorrhages, hard exudates, neovascularisation and microaneurysms.

By using a 50-degree angle of view digital fundus camera, the retinal pictures were captured and stored in PNG format, with 1500 × 1152 pixels density [13]. A research group from Lappeenranta University of Technology, Finland called The Machine Vision and Pattern Recognition, released this dataset, subsequently developed an additional dataset, named as the Standard Diabetic Retinopathy Database Calibration Level 1 (DIARETDB1) [14]. The dataset comprises 89 color eye fundus pictures, of which 84 display non proliferative diabetic retinopathy slight lesions, alongside five images classified as normal (no signs of diabetic retinopathy) [14]. However, both the DIARETDB1 and DIARETDB0 datasets offer a limited number of pictures, rendering them insufficient for the development of highly effective automated detection systems as a result of their small data volume.

The MESSIDOR dataset is a publicly accessible dataset, specifically intended to facilitate the assessment of indexing and segmentation methodologies in ophthalmology. It was supplied by the French Research and Defense Ministry to advance revisions on the diagnosis of diabetic retinopathy [15]. The dataset comprises 1,200 color eye fundus images, with a 45-degree angled view, captured using a color video 3CCD camera which mounted on a non-mydriatic device Topcon TRC NW6 model. The images are available in three different resolutions: 2304 × 1536 pixels, 1440 × 960 pixels, and 2240 × 1488 pixels, all represented in 8-bit color [15]. Messidor-2, another publicly available resource, is easily accessible by researchers to benchmark DR detection methods. It includes 1,748 color fundus images, on top of those in the original dataset.

DRIVE, or the Digital Retinal Images for Vessel Extraction, database is alternative important resource, providing color fundus images envisioned for the blood vessels automatic segmentation [16]. The dataset includes 40 images, of which 33 exhibit no diabetic retinopathy signs, while the other 7 display features of mild diabetic retinopathy stage. The images with 45-degree range of vision were captured with a non-mydratic camera Canon CR5 3CCD model, have a 768 x 584 pixels resolution and are represented in 8-bit color [16].

A research work conducted at the University of California, San Diego [17], created the STructured Analysis of the Retina (STARE) eye fundus image database. The dataset includes 400 color fundus images, each with diagnostic codes and associated diagnosis. Of these, 80 pictures are used for detection of optic nerve [17], and 40 images are specifically set aside for the segmentation of blood vessel tasks [18].

The DRIVE and STARE databases are valuable for retinal vessel segmentation, but neither includes measurements of vessel width. To narrow this difference, the REVIEW (REtinal Vessel Image set for Estimation of Widths) [19] was developed. This dataset contains 193 vessel segments taken from 16 images, covering a variety of vessel types and pathologies. It provides precise width measurements and sorts the images into four categories: vascular disease, high resolution, kick-points and central light reflex. The process for generating vessel profiles from the REVIEW database is described in detail by Al-Diri and colleagues [19].

The Retinopathy Online Challenge (ROC) highlighted various techniques for detecting microaneurysms [20]. The competition dataset comprises 50 training images and further 50 testing images, each supplemented by a reference standard. The images are available in three different resolutions: 1389 × 1383 pixels, 768 × 576 pixels, and 1058 × 1061 pixels. The competition's results showed that detecting microaneurysms continues to be a major challenge for both automated systems and human experts alike.

In the UK, the UHB Eye Image Dataset Release 001, put together by the University Hospitals Birmingham, is a key resource for studying diabetic retinopathy. It includes around seven million retinal fundus images and 440,000 OCT scans collected between 2007 to 2019 [21]. Alongside these images, the dataset provides detailed clinical information, such as patient demographics, visual acuity scores, and diabetic retinopathy grades (R0M0 to R3M1), as well as up to fifteen years of follow-up data, making it an invaluable tool for understanding disease progression and developing AI models. Similarly, diabetic eye screening captures ocular images and retinopathy grades. Between 2020 and 2021, the Solihull, Black Country, and Birmingham Diabetic Retinopathy Screening Programme collected over six million fundus images from more than 20,000 patients [21]. Each image comes with annual screening results and grading notes, creating a comprehensive dataset that helps evaluate population-level screening programs and validate AI tools.

The Mobile Brazilian Retinal Dataset (mBRSET) is the first set of retinal fundus images taken with portable retinal cameras. It is a diversified group of patients from Itabuna, Bahia, Brazil, and it has a lot of clinical and demographic information. The dataset includes 5,164 pictures from 1,291 people who have diabetes [22]. Its main value lies in helping develop and test computer vision algorithms designed for portable imaging devices, tools that are becoming increasingly important for screening and diagnosis.

An extensive diabetic retinopathy public dataset is the Diabetic Retinopathy Detection Kaggle dataset, offered by EyePACS [23]. This contains 88,702 images high-resolution retinal image captured using a variety of cameras, with both right and left fields provided for each subject. The occurrence of diabetic retinopathy in each picture is graded according to the 5-point scale: mild, moderate, severe, proliferative diabetic retinopathy, and no diabetic retinopathy. This dataset is particularly valuable for applications of deep learning, which necessitate large volumes of labelled data. However, Tariq et al. [24] found that this dataset has compelling challenges, such as wrong annotations, image noise and imbalanced classes.

Comprising a significant number of retinal images taken under various imaging settings using fundus photography, the APTOS 2019 Blindness Detection dataset - a more recent addition to diabetic retinopathy research - is accessible via Kaggle [25]. Where 0 shows no indications of the disease and 4 relates to proliferative diabetic retinopathy, every image has been clinically rated for the diabetic retinopathy severity on a 0 to 4 scale. In particular, this collection contains a private test set including over 13,000 photos, or around 20GB of data.

The Dataset of Retinal Blood Vessels collected from diabetic retinopathy and healthy persons consists of a succinct yet comprehensive collection of 50 fundus images, comprising 36 from persons with diabetic retinopathy and 14 from healthy controls [26]. The dataset contains extracted retinal vascular structures, serving as a focused and significant resource for examining vascular morphology and its pathological changes related to diabetic retinopathy.

Furthermore, Rahim et al. [27] collected a dataset sourced from the Eye Clinic of the Department of Ophthalmology at Melaka Hospital, Malaysia, consisting of both diabetic retinopathy (DR) and non-DR eye fundus images. This dataset, comprises 600 color fundus pictures, derived from 300 patient records, with at least two pictures per patient - one from the left eye and one from the right side, captured at two distinct angles, specifically centered on the macula or the optic disc. The original pictures are stored in JPEG format at a high resolution of 3872 × 2592 pixels, captured with a digital fundus camera KOWA VX-10 model, ensuring detailed and high-quality imagery. Three ophthalmologists from the Department of Ophthalmology, Melaka Hospital engaged in the classification of eye fundus pictures into ten retinopathy categories: No DR, Mild DR with maculopathy, Moderate DR with maculopathy, Severe DR with maculopathy, Proliferative DR with maculopathy, Mild DR without maculopathy, Moderate DR without maculopathy, Severe DR without maculopathy, Proliferative DR without maculopathy, and Advanced Diabetic Eye Disease. Each image was annotated independently by three specialists, employing a majority vote approach to get a more reliable classification. This dataset specifically represents the South Asian population, in contrast to several freely available datasets that predominantly feature Caucasian peoples.

Likewise, the database developed by Rahim and others [27], which it is representative for the population of Malaysia, another ethnicity-specific dataset has been introduced: IDRiD (Indian Diabetic Retinopathy Image Dataset) [28], known to be representative for the Indian population. The developed dataset comprises 516 eye fundus images stored in format of JPEG with 4288 × 2848 pixels high definition. A Kowa VX-10 alpha digital fundus camera model with a 50-degree perspective was used to capture the images, located at the Eye Clinic in Nanded, Maharashtra, India. All images are macula-centered. The dataset includes expert annotations of typical diabetic retinopathy signs, as well as information on the diabetic retinopathy severity level and the diabetic macular oedema presence for each image.

The Diabetic Retinopathy Dataset by Prabhat [29] comprises color fundus images grouped into five DR severity levels. No DR images (1,805) are for healthy retinas, while Mild (370 images) show early signs like microaneurysms. Moderate (999 images) reflects disease progression with haemorrhages and exudates. Severe (193 images) captures extensive retinal damage, and Proliferative DR (295 images) represents the most advanced stage, characterized by neovascularisation and high risk of vision loss.

The TJDR Dataset is produced by Tongji Hospital in China, which contains 561 high-quality fundus images precisely annotated at the pixel level [30]. It provides precise delineations for various retinal signs, including haemorrhages, cotton wool spots, hard exudates and microaneurysms, offering a rigorous foundation for diabetic retinopathy semantic segmentation research.

It can be summarized that, alongside the advancement of automated systems for diabetic retinopathy screening, a significant number of researchers have also produced and supplied eye fundus picture databases to facilitate research in retinal imaging and image manipulation, particularly for the purpose of diabetic retinopathy uncovering and screening. Moreover, these databases are beneficial not just for the screening of diabetic retinopathy purpose, but nonetheless for identifying other visual conditions, including hypertensive retinopathy, cataracts, and glaucoma. Table 1 shows an overview of widely retinal imaging datasets, including the country of origin, dataset name, image count, classification scheme, and primary application in eye disease detection.

4. AI for Diabetic Retinopathy and Related Eye Disease Image Processing

Monitoring and detection of ophthalmic diseases, particularly diabetic retinopathy (DR), are dependent on advanced image processing techniques. DR is a significant reason of (preventable) blindness that arises globally. In the initial DR-related signs disclosure, for example exudates, microaneurysms, and haemorrhages, as well as during the progression of the disease, computer-aided diagnostic (CAD) systems have demonstrated high sensitivity and specificity. Primary and accurate detection is necessary for the suitable initiation of treatment, which in turn reduces the risk of irreversible retinal injury and preserves functional vision. In underserved areas with restricted access to specialist care, the deployment of fully automated DR grading systems has the potential to enhance diagnostic throughput, standardize clinical assessments, and facilitate cost-effective population-level screening.

Diabetic retinopathy (DR) detection and screening remains an important and rapidly developing area of research. Early developments in diabetic retinopathy screening have mainly concentrated on retinal images classification, i.e., detecting the existence or absence of diabetic retinopathy [31-51]. To enable more granular detection of pathological features for instance exudates, microaneurysms, haemorrhages, and other retinal abnormalities, a large area of image processing approaches has been proposed and implemented [52-87]. In parallel, several studies have addressed the finding of maculopathy - characterised by yellowish lesions near the macula, which represents a critical aspect of DR management due to its association with progressive vision loss if left untreated [88-99]. Many methods that combine traditional and cutting-edge computational techniques have been succesfully established to

Table 1. Retinal image public databases summary.

Author [Ref.]	Country	Name of Dataset	No. of Images	Classes	Eye Disease Detection Purpose
Kauppi et al. [13]	Finland	DIARETDB0	130	Normal (20), DR with lesions (110)	Diabetic retinopathy (microaneurysms, exudates, haemorrhages, neovascularisation)
Kauppi et al. [14]	Finland	DIARETDB1	89	Normal (5), Mild NPDR (84)	Early diabetic retinopathy detection
Decencière et al. [15]	France	MESSIDOR / MESSIDOR-2	1,200 (MESSIDOR), 1,748 (MESSIDOR-2)	Multiple DR grades	Diabetic retinopathy grading and benchmarking
Staal et al. [16]	Netherlands	DRIVE	40	Mild DR (7), Normal (33)	DR detection, Retinal vessel segmentation
Hoover et al. [17, 18]	USA	STARE	400	Multiple diagnoses	Optic nerve detection, vessel segmentation
Al-Diri et al. [19]	UK	REVIEW	193 vessel segments (16 images)	Vessel subgroups	Vessel width estimation and analysis
Niemeijer et al. [20]	International (Challenge)	ROC (Retinopathy Online Challenge)	100 (50 training, 50 testing)	Microaneurysm detection	Evaluation of automated detection methods
UHB NHS Trust [21]	UK	UHB Eye Image Dataset Release 001	~7 million fundus images + 440k OCT scans	R0M0 to R3M1	DR progression, AI development, population-level screening
Jingxin et al. [22]	China	TJDR	561	Pixel-level lesion annotations	Semantic segmentation of DR lesions

Author [Ref.]	Country	Name of Dataset	No. of Images	Classes	Eye Disease Detection Purpose
EyePACS [23]	USA (Kaggle)	Diabetic Retinopathy Detection (Kaggle)	88,702	No DR, Severe, Moderate, Mild, Proliferative DR	Large-scale detection of DR, deep learning
APTOS [25]	International (Kaggle)	APTOS 2019 Blindness Detection	>13,000 (test set), full dataset ~20GB	DR severity (0–4)	DR grading and blindness detection
Akande [26]	Nigeria	Diabetic Retinopathy Image Database (DRiDB)	50	DR (36), Healthy (14)	Retinal vascular morphology in DR
Rahim et al. [27]	Malaysia	Melaka Hospital DR Dataset	600 (from 300 patients)	10 categories (No DR to ADED)	Comprehensive DR and maculopathy detection (South Asian population)
Porwal et al. [28]	India	IDRiD	516	DR severity + DME presence	DR and diabetic macular oedema (Indian population)
Prabhat [29]	India	Diabetic Retinopathy Dataset	3,662	No DR (1,805), Mild (370), Moderate (999), Severe (193), Proliferative (295)	DR severity classification
Nakayama et al. [30]	Brazil	mBRSET (Mobile Brazilian Retinal Dataset)	5,164	Multiple DR grades	DR screening with portable fundus cameras

increase the validity of maculopathy identification systems [88-99]. In general, a combination of feature extraction algorithms, machine learning-based classification techniques, and image pre-processing techniques has been utilized to create reliable and accurate DR detection systems. Ongoing research is also bringing new ideas to improve diagnostic performance.

Recent research on diabetic retinopathy has reported significant advances in both binary and multi-class classification approaches [31-38]. In parallel, progress in retinal image processing methods for the pathological detection of features; such as haemorrhages, microaneurysms, and exudates has been described in several studies [39-48]. Furthermore, developments of image processing methods application for the analysis of diabetic maculopathy have been introduced in the literature [49-55].

The sub-sections bellow discusses the range of AI techniques employed in eye disease detection, with particular emphasis on the feature extraction, image pre-processing, and classification stages.

4.1. Diabetic Retinopathy Image Pre-processing

Image preprocessing techniques are essential for the automated diabetic retinopathy (DR) and maculopathy detection, as they substantially impact the accuracy and robustness of downstream classification and feature extraction tasks. The primary intention of pre-processing implementation is to refine the quality of image, reduce noise, correction of illumination defects, and standardize the input data. These steps mutually simplify the more reliable pathological features identification such as exudates, microaneurysms, and haemorrhages.

In most pre-processing methods, the green channel is extracted because it has better contrast for retinal structures than the red or blue channels [27]. This makes it easier to tell the difference between lesions and blood vessels. Fuzzy image processing methods are able to handle the inherent uncertainty and unpredictability that come with medical imaging. Fuzzy filtering is one way to get rid of the noise and fuzzy histogram equalization can help increase the contrast. Also, fuzzy edge detection can show where the edges of lesions are. These methods have demonstrated significant improvements in image clarity and have substantially facilitated the accurate detection of maculopathy, particularly exudates in the macular region [27].

Image brightness and background intensity differences are often fixed with contrast enhancement and illumination adjustment, which are common pre-processing techniques. Under less-than-ideal imaging conditions [100, 101], these changes are necessary to protect the integrity of delicate disease features that might be hidden. Principal Component Analysis (PCA) technique is sometimes employed for dimensions reduction, helping to eliminate redundant or noisy data, which enhances computational efficiency and strengthens analytical reliability [102]. In sophisticated diagnostic frameworks, these methods are often incorporated into multi-stage processing pipelines, allowing for the collaborative use of complementary techniques to enhance overall system performance [103, 104].

Contrast-Limited Adaptive Histogram Equalization (CLAHE) remains fundamental in retinal image processing, achieving a vessel detection accuracy of 94% in green-channel fundus images [105]. In 2023, a significant development combines CLAHE with ESRGAN technique (Enhanced Super-Resolution Generative Adversarial Networks) to tackle the issue of identifying low-contrast exudates in underexposed areas, resulting in a 12% enhancement in classification F1-scores compared to CLAHE used independently [106]. In color-optimized diagnostic procedures, transformations into the color space enable the measurement of blue-channel dominance, attaining a diagnostic accuracy of 89.53%, and guiding adaptive contrast augmentation within the luminance channel [107].

Hybrid techniques employing median filter-based background estimation (with a kernel size of 15×15) in conjunction with homomorphic filtering have demonstrated a 68% reduction in intensity variation across unevenly illuminated fundus images [100, 107]. More recently, the normalized convolution-domain transform fusion method has advanced this domain further by suppressing artificial boundaries through multi-scale background modelling, attaining a pixel-level accuracy of 98.7% in fluorescein angiography (FFA)-based microaneurysm detection [108].

Fourth-order PDEs (partial differential equations) technique, when combined with median filtering, yield PSNR (peak signal-to-noise ratio) improvements of 3.89 dB in speckle noise reduction, while preserving the structural integrity of subretinal haemorrhages [107, 108]. Meanwhile, motion deblurring networks incorporating Wiener filter priors have demonstrated the ability to recover up to 92% of capillary detail in fundus images captured using handheld smartphone devices [107].

Within diabetic retinopathy detection systems, morphological operators - particularly erosion and dilation, are commonly utilized for the extraction of blood vessels. In pediatric applications, blood vessel erosion guided by U-Net segmentation enhances the visibility of retinopathy of prematurity (ROP) features by 22% in RetCam images [109].

These pre-processing strategies are fundamental to perform a reliable diabetic retinopathy and maculopathy detection, as they establish a critical foundation for accurate feature extraction and consistent classification. Their importance is particularly pronounced in large-scale screening programs, where image quality often exhibits significant variability [27, 104].

4.2. Feature Extraction

Feature extraction plays a critical role in the automated detection of diabetic retinopathy (DR) and maculopathy, enabling algorithms to recognize and quantify disease-relevant patterns within retinal images.

The process typically starts with the localization of key anatomical parts, including the retinal vasculature, optic disc, and macula. Optic disc correct identification is crucial for establishing a spatial reference and preventing misinterpretation of brilliant diseased lesions. Accurate identification of the macula and fovea is essential for assessing the closeness of anomalies to the central visual axis, a critical factor in grading maculopathy. Blood vessel segmentation enhances this procedure by differentiating normal vascular structures from diseased changes and averting the erroneous designation of vessels as lesions [110-112].

The automated discovery of maculopathy and diabetic retinopathy is predicated on the precise localization and characterization of retinal lesions. The earliest clinically observable indicators of diabetic retinopathy; microaneurysms, are typically detected using morphological operators and color-based thresholding. Their frequency and spatial distribution are critical metrics in the early stage of the disease.

Haemorrhages, which present with greater size and shape variability, are identified through region-based analysis, with particular emphasis on their proximity to the macula. Hard and soft exudates appear as high-intensity lesions and are delineated using features such as brightness, area, and compactness; their localization near the macula is a defining criterion for diabetic maculopathy. Cotton-wool spots are distinguished by their diffuse, cloud-like appearance and are indicative of localized retinal ischemia. In advanced systems, macular oedema is quantified either by assessing the extent of exudate accumulation in the foveal region or through retinal thickness measurements derived from optical coherence tomography (OCT) imaging [110-113].

In addition to lesion detection, a broad range of quantitative and textural features are extracted to improve diagnostic precision. These include morphological metrics such as lesion compactness, area, mean intensity, color variance, and mean hue, alongside frequency- and entropy-based descriptors derived from wavelet and Gabor transforms. Techniques for dimensionality reduction, predominantly PCA (Principal Component Analysis), are frequently implemented to reduce redundancy and isolate the most discriminative features [112]. Convolutional neural networks are among the utmost prominent contemporary techniques of deep learning that eliminate the requirement for manual feature creation and selection process, by automatically learning hierarchical representations from raw retinal images. These models are competent of capturing complex spatial forms and subtle visual signals that may unnoticeable through conventional methods. In the diabetic retinopathy detection presence and severity, convolutional neural networks-based systems have demonstrated diagnostic performance that is comparable to, and in some cases superior to, that of expert clinicians in large-scale validation studies [110, 114].

In the context of maculopathy detection, the spatial relationship between pathological lesions, such as exudates and haemorrhages, and the macula is of critical importance. Equally essential is the direct macular thickness assessment with optical coherence tomography (OCT) for the oedema identification. The incorporation of extensive feature extraction algorithms, utilizing both classical image processing methods and modern deep learning models, has considerably enhanced the specificity and sensitivity of automated screening systems for diabetic retinopathy and maculopathy [110-113, 115].

4.3. Deep Learning

Machine learning classifiers have become integral to the automated diabetic retinopathy (DR) and maculopathy detection and grading, offering scalable, rapid, and accurate screening solutions suitable for large populations. Typically serving as the final stage in a multi-step analytical pipeline - including image acquisition, pre-processing, anatomical localization, and feature extraction, these classifiers play a crucial role in overall system performance. The choice of an appropriate classifier, spanning conventional machine learning procedures to high-level deep learning models, significantly influences the accuracy, robustness, and clinical relevance of frameworks for detecting maculopathy and diabetic retinopathy. There are changes in both deep learning and conventional ways of doing things as the field grows. Each has it own perks that make it best for certain technical and clinical [116].

Deep learning has markedly advanced the automated diabetic retinopathy and maculopathy detection by enabling endwise feature learning and delivering advanced diagnostic accuracy. Convolutional Neural Networks (CNNs), including architectures such as ResNet, InceptionV3, and EfficientNet, are extensively utilized for DR severity classification, with reported accuracies exceeding 95% on large-scale public datasets [31, 36, 90, 116, 117]. The transfer learning application, and refining pre-trained models on retinal image datasets has enhanced performance and reduced computational costs, as evidenced by the effective deployment of DenseNet-121 and InceptionV3 for DR detection [31, 118, 119].

Recently, Vision Transformers (ViTs), such as SWIN-Tiny, have demonstrated superior effectiveness over CNNs in identifying referable diabetic retinopathy (DR), achieving area under the curve (AUC) values exceeding 97%, due to their capability to comprehend extended spatial dependencies in fundus images [31, 120]. Hybrid architectures, particularly Attention U-Net combined with Unfolded Deep Kernel Estimation (UDKE), have markedly enhanced retinal vascular segmentation, an essential process for the early intervention of maculopathy and diabetic retinopathy [31, 120]. The concurrent integration of deep recurrent neural networks (RNNs) and Bayesian deep learning methodologies has facilitated not only increased classification accuracy but also the assessment of predicted uncertainty, thus improving clinical interpretability and decision support [119, 121, 122].

Recent breakthroughs have integrated explainable artificial intelligence (XAI) approaches into deep learning classifiers, addressing concerns associated with the inherently opaque, "black box" nature of these models [31, 123]. Techniques for example Saliency Maps and Gradient-weighted Class Activation Mapping enable clinicians to visualize the specific areas of a retinal image that substantially influenced the model's evaluation, thereby enhancing interpretability, adopting clinical trust, and supporting validation efforts [123]. Simultaneously, ensemble deep learning approaches, either by integrating various architectures or combining outputs from models trained on diverse datasets, have exhibited enhanced robustness and generalizability, especially in multi-ethnic and multi-device screening scenarios [31, 121]. As a result, the maculopathy and diabetic retinopathy exploration with deep learning methods are progressively being validated in real-world clinical studies and advancing towards regulatory approval for wider clinical use [117].

The deep learning systems enhancing real-world diabetic retinopathy (DR) screening programs have demonstrated both feasibility and clinical efficacy. Exploratory studies indicate that such models can achieve sensitivity and specificity comparable to, or exceeding, that of trained ophthalmologists and regional retina specialists in identifying vision-threatening DR and diabetic macular oedema [117, 122]. Nonetheless, several challenges persist, remarkably the requirement for large, well annotated datasets and the limited interpretability of model outputs within clinical contexts, which may hinder trust and adoption among healthcare practitioners [120, 122].

4.4. Other Machine Learning Methods for Eye Fundus Image Processing

Conventional machine learning classifiers remain relevant for diabetic retinopathy (DR) detection despite them being largely used in this application before deep learning methods, especially in settings with constrained computational resources or when model interpretability is paramount. Support Vector Machines (SVM) and Random Forest and are commonly utilized algorithms with handcrafted features, exhibiting robust performance with classification accuracies reported between 76% and 89% in diabetic retinopathy risk prediction tasks [116, 121, 124].

K-Nearest Neighbors (KNN), often enhanced through dimensionality reduction techniques such as Logistic Regression and Principal Component Analysis (PCA), is also utilized. However, KNN performance is typically moderate and less suited to the detection of complex retinal lesions when compared with deep learning-based approaches [116, 124]. Other classifiers, such as the Restricted Boltzmann Machines (RBM) and Optimum-Path Forest (OPF) have been explored, with certain studies indicating diagnostic accuracies for RBM nearing 90% [121, 124]. Moreover, ensemble and hybrid models, which either integrate various classifiers or merge handmade characteristics with deep learning outputs, have demonstrated lot of potential in enhancing the robustness and generalizability of diabetic retinopathy detection systems [116, 124].

A significant strength of traditional machine learning classifiers lies in their transparency and interpretability, attributes that are highly valued in clinical decision-making processes [116]. Models for example logistic regression and decision trees provide explicit representations of how individual risk factors or image-derived features contribute to the final prediction, thereby enabling patient-specific risk assessment and the development of personalized management strategies [116, 124]. Additionally, these classifiers are computationally efficient and can be implemented in low-resource settings with limited access to sophisticated hardware or stable internet connectivity, rendering them particularly effective for deployment in rural and underserved regions [116]. While deep learning methods have demonstrated superior predictive performance, traditional classifiers are still necessary for the provision of interpretable, scalable, and practical solutions in the screening and detection of diabetic retinopathy and maculopathy [116].

In addition, the machine learning classifiers landscape for the maculopathy and diabetic retinopathy (DR) identification is undergoing continual advancement. Deep learning models, particularly those incorporating transfer learning and attention mechanisms have emerged as the benchmark for high-throughput, accurate screening. Nevertheless, traditional classifiers retain a meaningful role, especially in contexts requiring interpretable risk modelling or as integral components within ensemble frameworks. Their continued use contributes to making automated DR screening systems both accessible and adaptable across a range of clinical settings [116, 120, 122].

5. XAI for Eye Fundus Image Processing

The incorporation of explainable artificial intelligence (XAI) into eye fundus image analysis has gained growing significance, particularly as deep learning models, despite their impressive predictive accuracy, are frequently criticized for their lack of interpretability. XAI provides methods for clarifying the rationale behind the model prediction/classification for these otherwise inscrutable “black box” models, so bolstering clinical confidence and facilitating better informed decision-making in the automated assessment and diagnosis of diabetic retinopathy and other ocular disorders. XAI methods in eye fundus image processing enhance the interpretation of model outputs and enable the validation of algorithmic focus on clinically significant anatomical and pathological structures, such as lesions, the macula, and the retinal vasculature.

Several categories of XAI techniques are widely employed in fundus image analysis, each serving a distinct role in enhancing model interpretability:

Activation Mapping (e.g., CAM (Class Activation Mapping), Grad-CAM, Grad-CAM++, Layer-CAM, Score-CAM: The visualisation methods produce heatmaps that feature the regions of a fundus image most prominent in driving a model’s decision [125]. By superimposing these maps onto the original images, clinicians can validate whether the AI system relies on clinically relevant characteristics, such as exudates, microaneurysms, or haemorrhages, thereby facilitating the assessment of prediction reliability.

Feature Attribution Methods: Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) are employed to identify and quantify the impact of individual pixels, specific regions, or extracted image features (e.g., texture or colour statistics) on a model’s decision [126]. These methods are particularly effective when combining deep learning architectures with classical image processing descriptors, such as Gabor filters or local binary patterns. Consequently, they facilitate a more comprehensive and multi-dimensional diagnostic evaluation.

Model-Specific Insight Tools: For convolutional neural networks (CNNs) and vision transformers, techniques including saliency mapping, attention visualisation, and region-level representation analysis offer valuable insights into how models interpret subtle and spatially distributed pathological patterns in fundus images [127]. These methods enhance the understanding of model decision-making processes, particularly in identifying abnormalities linked to conditions namely glaucoma and diabetic retinopathy.

An explainable deep learning model for diabetic retinopathy was devised by Shahzad et al. [128] using a convolutional neural network and LIME for interpretability. This model achieved up to 94% higher accuracy than traditional methods and provided transparent, clinically relevant insights. Quellec et al. [129] introduced ExplAIn, an XAI framework for diabetic retinopathy that segments and classifies lesions using self-supervised foreground/background separation, enabling autonomous lesion identification and interpretable diagnostic explanations via pixel-level visualizations and textual summaries.

Herrero-Tudela et al. [130] suggested a model of deep-learning based on modified ResNet-50 for diabetic retinopathy, using SHAP to visualize critical retinal features, improving both diagnostic accuracy and clinical transparency. Marapelli et al. [131] integrated VGG16 with Grad-CAM for the detecting diabetic retinopathy, attaining an accuracy of 72% and providing visual elucidation of the model's decision process.

In their 2024 research work, Yagin et al. [132] developed a hybrid AI architecture integrating Support Vector Classification and a Multilayer Perceptron for the diabetic retinopathy detection, with an accuracy of 89.6%. SHAP was utilized to augment interpretability, identifying essential biomarkers such as glucose, glycine, and creatinine for enhanced clinical insights. Additional research studies employing XAI algorithms for the analysis of ocular fundus pictures to diagnose DR have been examined in [133-135].

Wang et al. [136] developed an explainable artificial intelligence (XAI) approach that uses medical Internet of Things (IoT) systems to expand the accuracy and reliability of detecting age-related macular degeneration (AMD). They introduced a deep learning model that combines XAI methods to perform well across different types of eye imaging, for example optical coherence tomography, color fundus photography, ultra-wide field fundus images, and fluorescein angiography. By making the model’s decisions easier to interpret and more adaptable, the use of XAI helped reduce overfitting and made automated AMD diagnosis more dependable in real clinical practice.

Osa-Sánchez et al. [137] established an AI-based method to diagnose age-related macular degeneration (AMD) in fundus images in 2025. The team extracted numerical characteristics from eye fundus images using Convolutional Neural Networks, Vision Transformers, and Multilayer Perceptrons in a cascaded model. The Multilayer Perceptron model was 91.86% accurate, 92.22% sensitive, and 95.74% specific. Combining XAI techniques with model decision-making transparency helped clinicians uncover microscopic retinal defects that signal AMD. This strategy increases automated AMD diagnostic interpretability for clinical decision-making and early intervention.

Abbas et al. [138] predicted eye issues with 95.74% accuracy using transfer learning. A technique called Local Interpretable Model-Agnostic Explanations (LIME) helped clinicians understand the decision analysis model process. This method makes standard AI models more transparent, enhancing ocular diagnostics trust and clinical integration.

Al Balawi et al. introduced IoT-Opthom-CAD [139], an IoT-based framework for classification of diverse retinal disorders for instance tessellation, age-related macular degeneration, hypertensive retinopathy, diabetic retinopathy, and optic disc edema employing dynamic Swin Transformers and LightGBM, and attaining 95% accuracy. The addition of Grad-CAM provided clear visual explanations, which improved clinical confidence and understanding of diagnoses.

Anvesh et al. recently developed a refined VGG16-based deep learning framework for the automated retinal fundus images classification into four categories: tessellated, myopic, choroidal neovascularization, and normal [140]. The purpose of the study is to improve classification accuracy; however, it also incorporates Grad-CAM to specify visual representations of the model's solving process. This integration provides clinicians with transparent insights into the regions of interest within fundus images, thereby enabling them to make more accurate and interpretable diagnostic decisions.

Vieira et al. [141] employed LIME and SHAP to elucidate CNN-based glaucoma detection, offering visual interpretations derived from retinographic images. Conversely, Velpula et al. [142] used Grad-CAM with CNN and machine learning classifiers to show important features of the retina. These studies collectively demonstrate how XAI approaches enhance transparency and clinical trust in automated glaucoma diagnosis.

The XAI strategies that have been employed in the area of eye fundus digital imaging analysis in order to detect and evaluate ophthalmic diseases are summarized in Table 2. Researchers and clinicians are able to validate and enhance deep learning models by integrating these XAI techniques into eye fundus image analysis workflows. This integration is essential for improving dependable AI solutions in ophthalmology, and vital for adherence to regulatory standards and facilitating efficient application in clinical practice. Figure 2 presents a visual overview diagram of an AI and XAI pipeline for diabetic retinopathy screening.

6. Conclusions

Development of automated AI-based diagnostic systems is a major area of interest for medicine and health in general, and especially for ophthalmic disease screening and detection. Several studies have been undertaken to establish reliable AI methods for identifying specific aspects of eye diseases using retinal fundus pictures. Although substantial progress has been achieved in the past years, there are still significant gaps and opportunities for further development and refinement.

The methods presented in this literature review provide valuable contributions to the field of image processing, particularly by advancing accurate and efficient methods for the detection of pathological features associated with ophthalmic diseases. There are a lot of image processing techniques out there that can be used, but there is still a huge need for techniques that are especially designed and optimized for finding eye diseases in the retinal fundus pictures. It is very important that the classification methods used work well in order to make eye disease grading more accurate and reliable.

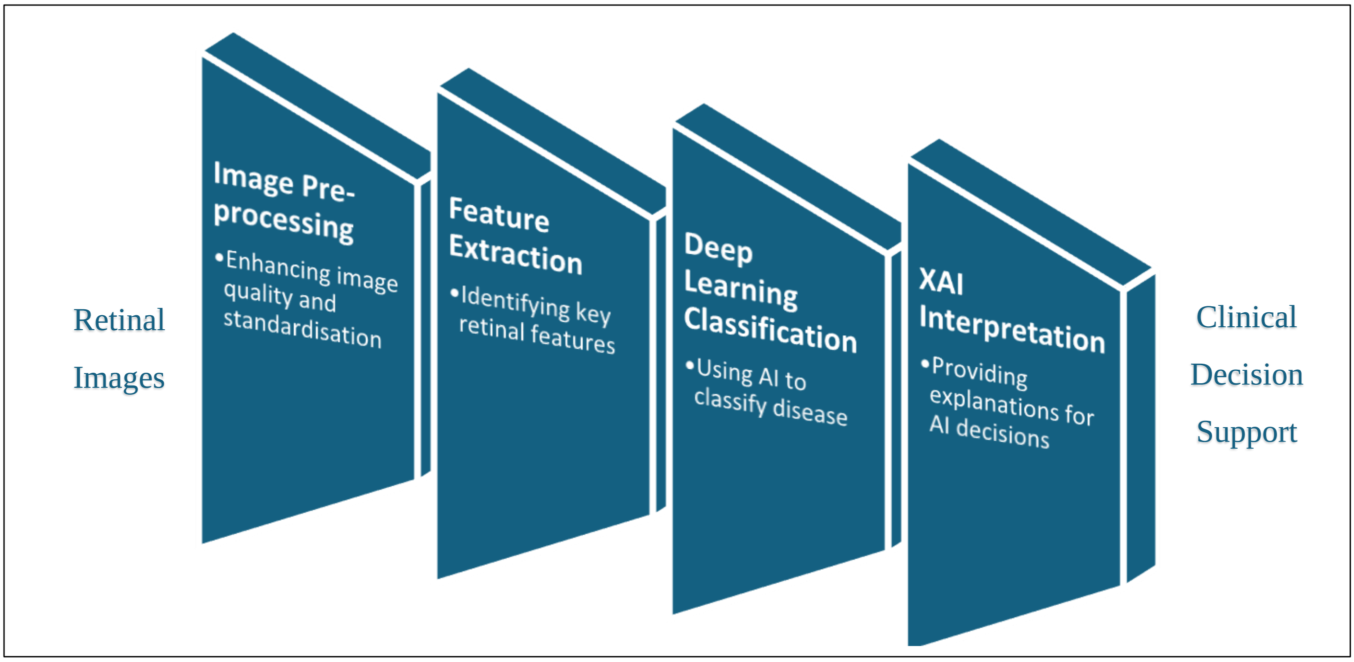

Fig. 2. General scheme for AI/XAI driven diabetic retinopathy detection.

Table 2. Summary of XAI techniques applied to eye fundus image analysis for ophthalmic disease detection.

Author [Ref.]	Eye Disease Detected	XAI Techniques Used	Capability / Contribution of XAI Techniques
Shahzad et al. [128]	Diabetic retinopathy (DR)	LIME	Achieved 94% accuracy; provided transparent, clinically relevant lesion visualizations, enhancing interpretability and trust.
Quellec et al. [129]	Diabetic retinopathy	ExplAIn (self-supervised lesion segmentation + visual/textual explanations)	Enabled autonomous lesion detection with pixel-level visualizations and interpretable diagnostic summaries.
Herrero-Tudela et al. [130]	Diabetic retinopathy	SHAP	Highlighted critical retinal regions influencing predictions, improving diagnostic transparency and clinical interpretability.
Marapelli et al. [131]	Diabetic retinopathy	Grad-CAM (VGG16-based)	Achieved 72% accuracy; provided heatmaps showing lesion-specific activations, supporting clinician trust.
Yagin et al. [132]	Diabetic retinopathy	SHAP	Hybrid model (SVC + MLP) with 89.6% accuracy; SHAP identified significant biomarkers (e.g., glucose, glycine, creatinine) for better clinical decision-making.
Obayya et al. [133]	Diabetic retinopathy	SHAP + Grad-CAM	Enhanced grading and classification accuracy in teleophthalmology; provided lesion-focused visual explanations.
Ahnaf Alavee et al. [134]	Diabetic retinopathy	Integrated XAI with DL models	Improved early DR detection; explained lesion relevance and supported clinical trust in AI-assisted screening.
Gautam and Shanker [135]	Diabetic retinopathy	Survey of XAI methods	Comprehensive review of XAI-enabled DR detection; highlighted key techniques for grading, segmentation, and interpretability.
Wang et al. [136]	Age-related macular degeneration (AMD)	Integrated XAI framework	Applied across multiple imaging modalities; enhanced interpretability, generalization, and reliability of automated AMD detection.
Osa-Sánchez et al. [137]	AMD	Vision Transformers + CNN + MLP with integrated XAI	Achieved 91.86% accuracy, 92.22% sensitivity, 95.74% specificity; provided transparent insights into subtle retinal changes for early AMD progression detection.
Abbas et al. [138]	Hypertension, myopia, AMD, glaucoma, cataract, diabetes, other, normal	LIME	Achieved 95.74% accuracy; provided interpretable feature contributions, enabling explainable predictions and improved clinician confidence.
Al Balawi et al. [139]	DR, AMD, optic disc oedema, hypertensive retinopathy, tessellation	Grad-CAM (IoT-Opthom-CAD framework)	Attained 95% accuracy; Grad-CAM highlighted lesion-relevant retinal regions, improving clinical explainability and diagnostic confidence.
Anvesh et al. [140]	Myopic CNV, tessellation, normal retina, other retinal disorders	Grad-CAM (VGG16-based)	Enabled four-class classification; provided visual explanations of model decisions to support informed clinical assessments.
Vieira et al. [141]	Glaucoma	LIME + SHAP	Delivered comparative visual and numerical explanations of CNN-based predictions, enhancing transparency and clinical usability.
Velpula et al. [142]	Glaucoma	Grad-CAM + CNN + ML classifiers	Highlighted discriminative retinal features; improved interpretability and supported clinician-driven glaucoma detection.

A concise summary of the key AI and XAI methods has been provided in this review, highlighting the primary approaches used for diabetic retinopathy detection and other eye diseases, including traditional machine learning, deep learning, and hybrid models. The discussion also looked at how explainable AI can make decisions easier to understand and help doctors feel more confident in using AI systems in this application.

Diabetic retinopathy screening is fundamentally challenging since it requires the identification and detection of a wide variety of clinical indications or signs to achieve a comprehensive and effective diagnosis process. Identifying these signs is challenging because each feature of the disease has its own distinct appearance. As a result, screening for diabetic retinopathy is not a simple process. Before a clinical diagnosis can be made, several factors must be carefully examined and evaluated in detail.

To ease the strain of manual screening and make automated systems more effective, there is a clear need for smarter and more efficient computational methods. Because diabetic retinopathy is complex and difficult to be detected automatically, combining modern image processing with advanced AI and XAI algorithms could offer faster learning, greater accuracy, and more reliable diagnostic results.

7. Future Directions

The latest progress in deep learning and computer vision approaches have positively improved automated diabetic retinopathy screening; yet, substantial technological and practical obstacles persist. Image processing techniques must address significant variation in retinal image quality as a result of differences in acquisition devices, patient adherence, lighting inconsistencies, and opacities in ocular media. Furthermore, extremely accurate segmentation techniques and algorithms that are resistant to noise and artefacts are necessary for the successful identification of small and often undetectable pathological signs, in particular cotton wool spots, hard exudates, and microaneurysms. These issues highlight the urgent need to develop standardized, robust image enhancement and pre-processing pipelines that can handle the diversity found in actual clinical datasets.

Machine learning methodologies are similarly confronted with significant constraints in terms of their clinical applicability, transparency, and generalizability. Many contemporary models, in particular deep learning models, are predicated on extensive, meticulously curated datasets that may not accurately reflect the heterogeneity of patient populations, imaging devices, and disease progression. Furthermore, the opaque decision-making processes of many deep learning systems restrict their use in therapeutic settings, where interpretability and accountability are critical. Future research must prioritize the development of ethically sound data augmentation techniques, cross-domain validation strategies, and explainable AI frameworks to ensure the reliable deployment of automated eye disease detection systems in real-world healthcare settings.

Author Contributions

S.S.R. was responsible for the conceptualization and drafted the manuscript. R.W. and K.K. were responsible for the resources and manuscript writing. V.P. was responsible for overall supervision and manuscript writing and revision; all authors reviewed and approved the final version.

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Conflict of Interest:

The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
XAI	Explainable Artificial Intelligence
DR	Diabetic Retinopathy
CAM	Class Activation Mapping
SHAP	Shapley Additive Explanations
LIME	Local Interpretable Model-Agnostic Explanations
CNN	Convolutional Neural Network
DL	Deep Learning
ML	Machine Learning

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