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REVIEW ARTICLE

Analysis of Deep Learning Techniques for Prediction of Eye Diseases: A Systematic Review

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Abstract
The prediction and early diagnosis of eye diseases are critical for effective treatment and prevention of vision loss. The identification of eye diseases has recently been the subject of much advanced research. Vision problems can significantly affect a person's quality of life, limiting their ability to perform daily activities, impacting their independence, and leading to emotional and psychological distress. Lack of timely and accurate identification of the cause of vision problems can lead to significant challenges and consequences. Delayed diagnosis prolongs the period of impaired vision and its associated negative impact on an individual's well-being. Deep learning techniques have emerged as powerful tools for analyzing medical images, including retinal images and predicting various eye diseases. This review provides an analysis of deep learning techniques commonly used for eye disease prediction. The techniques discussed include Convolutional Neural Networks (CNNs), Transfer Learning, Generative Adversarial Networks (GANs), Recurrent Neural Networks (RNNs), Attention Mechanisms, and Explainable Deep Learning. The application of these techniques in eye disease prediction is explored, highlighting their strengths and potential contributions. The review emphasizes the importance of collaborative efforts between deep learning researchers and healthcare professionals to ensure the safe and effective integration of these techniques. The analysis highlights the promise of deep learning in advancing the field of eye disease prediction and its potential to improve patient outcomes.

1 Introduction

The five primary sense organs of the human body are the nose, ear, hands, mouth and eyes. The eyes of all four sense organs support the visual perception of an environment. The eye is a very delicate organ that requires extreme care in handling. About 15 million people are blind in India, and the horrible truth is that 75% of these cases can be cured. Medication is less successful in preventing vision impairing, patients with ocular disorders frequently unconscious and silent development of diseases. Despite the fact that routine eye exams allow for early diagnosis and prompt treatment of many disorders, they would place a huge burden on the already scarce diagnostic facilities. Computer-aided diagnosis (CAD) solutions that reorganize the technique of eye illness detection are required immediately to reduce the pressure on clinicians. Due to the rapid technological development of hardware and software, numerous CAD systems for the detection of eye diseases have been established in recent years. However, most are still under analysis or clinical validation [1, 2].

Since the eyes have certain nerve fibres and light-sensitive cells, light rays can travel from the eye to the brain as nerve impulses. A thin sheet of tissue called the retina at the back of the eye offers the central vision required for everyday activities. A number of illnesses can impair the retina according to the patient's age. It is now essential to detect retinal illnesses because if the illness is not identified at an early stage, many people risk going blind. The clinical routine, including diagnosis, monitoring and treatment, is now made more difficult by the growing volume of patient data. Several eye diseases (ED), such as diabetic retinopathy (DR), cataracts, glaucoma, age related macular degeneration (AMD), Diabetic macular edema (DME) and so on, are together referred to as eye diseases [3].

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1.1 Different Eye Diseases

1.1.1 Diabetic Retinopathy

An eye ailment known as diabetic retinopathy develops after having diabetes mellitus for a number of years. It damages the small veins in the retina, which causes the veins to become obstructed, damaged, and grow randomly. Due to elevated blood sugar levels, a side effect of diabetes is when the blood vessels in the eyes begin to narrow. Blindness may result from decreased blood flow to the retina. Lesions that form on the retinal surface are among the signs of DR. Proliferative diabetic retinopathy (PDR) and Non-proliferative diabetic retinopathy (NPDR) are the two distinct phases of DR. The first stage of DR is NDPR. Now, the retina's veins are becoming brittle and releasing retinal fluid, which causes microaneurysms (MAs). In the course of DR, several lesions develop. The initial sign of diabetic retinopathy is a microaneurysm, which appears as tiny red dots on the retina and forms when weak veins expand. When all blood arteries are fully blocked, aberrant blood vessels known as PDR grow in order to provide the retina with the necessary oxygen. The final stage of DR is PDR. During this stage, the vision of the eye is completely lost. Although DR cannot be cured, its high prevalence can be managed with medication. Therefore, routine eye screening is crucial for the early identification of DR [4–10].

1.1.2 Glaucoma

Optic neuropathy or glaucoma causes dynamic damage to the optic nerve and leads to poor eyesight. An increase in intraocular pressure in the eyeball is a symptom of glaucoma. Glaucoma could damage the optic nerve. When it gets to an advanced level, it's obvious. Glaucoma can be detected when a patient has lost 70% of their vision. Therefore, it is important to regularly examine the eyes for glaucoma. There are three types of glaucoma: primary/open angle glaucoma, angle closure glaucoma, and common pressure. The most common form of glaucoma is primary-angle glaucoma. In this type of glaucoma, the eye's seepage system becomes inadequate over time. The weight in the eye increases continuously due to this drop in the seepage structure. A less common form of glaucoma is angle-closure glaucoma. This glaucoma blocks the back of the eye. Normal-strain Glaucoma causes optic nerve damage even though the eye weight remains within normal limits [11–13].

1.1.3 Cataract

A cataract is an eye disorder resulting from the focal point's blurring. Cataract is a simple eye condition caused by a focused protein that has accumulated over a long period of time. Moreover, the cataract prevents light from shining through the viewpoint and impairs eyesight. Depending on the region, cataracts can be divided into three categories: normal, cortical, and sub-capsular cataracts. The most common type of cataract is a normal cataract. It develops someplace deep within the focal point's focal zone. The focal point causes the cortex to become cloudy, resulting in a cortical cataract. Cracking occurs when fluctuations in water content occur around the focal point. This type of cataract is more likely to develop in those with diabetes or those who take high doses of steroid medication [14–16].

1.1.4 Age-Related Macular Degeneration

Degeneration: AMD affects vision in the center while blurring and distortion occur in the peripheral areas. AMD is divided into wet AMD (exudative AMD) and dry AMD (non-exudative AMD), depending on whether exudates are present due to dry AMD, the retinal pigment epithelium under the retina deteriorates. The retina's central photoreceptors are lost, resulting in vision loss. Drusen, or subretinal deposits formed by retinal waste products, are the main symptom and the first clinical sign of dry AMD. Wet AMD causes vision loss due to abnormal blood vessel growth in the choriocapillaris that runs through Bruch's membrane, eventually causing blood and protein leaks beneath the macula. If ignored, the leakage, scarring, and bleeding from these blood vessels eventually permanently destroy the photoreceptors and cause sudden vision loss. Exudation is the main sign of wet AMD [17, 18].

1.1.5 Diabetic Macular Edema

One of the greatest difficult and chronic eye conditions, DME is a leading cause of permanent blindness around the globe. DME occurs when fluid builds up in the macular area of the retina as a result of a blood vessel injury. Sharp, straight-ahead vision is made possible by the macula. The macula swells and thickens due to fluid accumulation, causing vision distortion. Based on the retinal thickness and hard exudates, the phases of DME can be divided into mild, severe and moderate. Initial recognition and action will help to stop significant vision loss [19, 20].

All eye diseases can cause significant vision loss and blindness in patients between 20 and 74. Optic nerve obstruction, abnormal blood vessel growth and the development of hard exudates in the macular region are the first symptoms of severe eye disease [21–23]. Numerous disease detection and classification systems combine data from medical tests and expertise. However, most systems do not link the relevant diseases to symptoms and clinical findings. While eye diseases often do not pose a life-threatening threat, their progression over time can significantly impact the patient's quality of life. Ophthalmological tools are used to perform physical tests, and thorough interpretation is used to make a diagnosis. In the medical industry, automating screening and diagnosis saves time, reduces the possibility of misdiagnosis, and lowers physician labour and financial costs [24–26].

Automation is progressing rapidly due to the feasibility and growth of DL and machine learning (ML) methods that enable machines to understand complicated aspects of medical data. Optical coherence tomography (OCT), fundus imaging, ultrasound, etc., are different imaging modalities. The light reflected from the inner surface of the eye is captured by an image sensor built into a complex microscope used for fundus imaging. This optical system allows medical professionals to see the eye's major biological landmarks and intricate background patterns that are the inner components of the retina. Confocal microscopy and interferometry concepts are combined in the non-invasive imaging technique OCT. Images of the retinal background are also used to look for eye disorders and to diagnose organ failure due to vascular disorders such as diabetes mellitus and hypertension. With the help of images from both types of devices, ophthalmologists can examine the eyes of patients and identify retinal diseases. These images also serve as a basis for creating eye applications [27–34]. The following list includes many imaging systems used to diagnose eye diseases.

1.2 Various Types of ML and DL Techniques Employed in Eye Disease Classification

Various types of ML and DL methods are employed in eye disease classification. Different machine learning techniques utilized in existing techniques are logistic regression, Adaboost, Naive Bayes, neural networks, support vector machine (SVM), linear discriminant examination, genetic algorithm, hidden Markov model, decision tree, random forest and others. Subsequently, various deep learning based techniques used in eye disease classification are the convolutional neural network, residual network, Dense Network, long short term memory, recurrent neural network, VGG network, and inception network.

Various deep learning techniques used in eye disease classification are convolutional neural network (CNN), deep neural network (DNN), deep convolutional neural network (DCNN), VGG framework, dense network, residual network and Inception network. Various existing ML and DL methods used in eye disease calculation are shown in Figs. 1a and b.

1.3 Different Modalities for Eye Disease prediction

1.3.1 Ultrasound

Ultrasound is a term used to describe sound waves with frequencies that are outside of the human ear. This treatment aids in the recognition of visual impairments, including retinal detachment, eye tumours, and neoplasms, as well as the identification of diseases [34–36].

1.3.2 OCT

OCT is another alternative invention for achieving high resolution cross-sectional scanning of internal human tissue. OCT is almost identical to two imaging modalities: confocal microscopy and ultrasound imaging, which uses light instead of sound. OCT imaging is commonly used to visualize the internal parts of the eye, such as the RNFL, macula, blood vessels, optic nerve and fovea, as well as to examine the morphology and count variations in the eye [37–40].

1.3.3 Fundus Photography

To record the occurrence of eyeballs and to monitor their evolution over time, retinal fundus photography uses a fundus camera to capture color images of the fundus, the inner part of the eye. The dorsal post, retina, retinal veins, fovea, macula, and optic disc (OD) can also be photographed in the eye with a retinal fundus camera, which is an extra-low-power microscope with a dedicated camera. The optical project of fundus cameras is determined by the guideline for monocular indirect ophthalmoscopy [41–44].

1.3.4 Heidelberg Retinal Tomography (HRT)

A non-invasive examination technique that uses confocal laser perversion microscopy to take precise measurements for precise observation and documentation of the interior eye. An accurate observation is essential for the diagnosis and treatment of eye diseases, such as a 3D image of the entire optic nerve, the device composes each of these images of layers [45].

The diagnostic features to be studied are included in Table 1, along with several imaging technologies that can be utilized to detect each eye illness. In most research, only OCT and Fundus photography have been used immensely. Only studies that solely employed OCT and fundus photography as a modality were reviewed for this study.

Image processing (IP) based techniques for automated identification and diagnosis of various eye diseases have

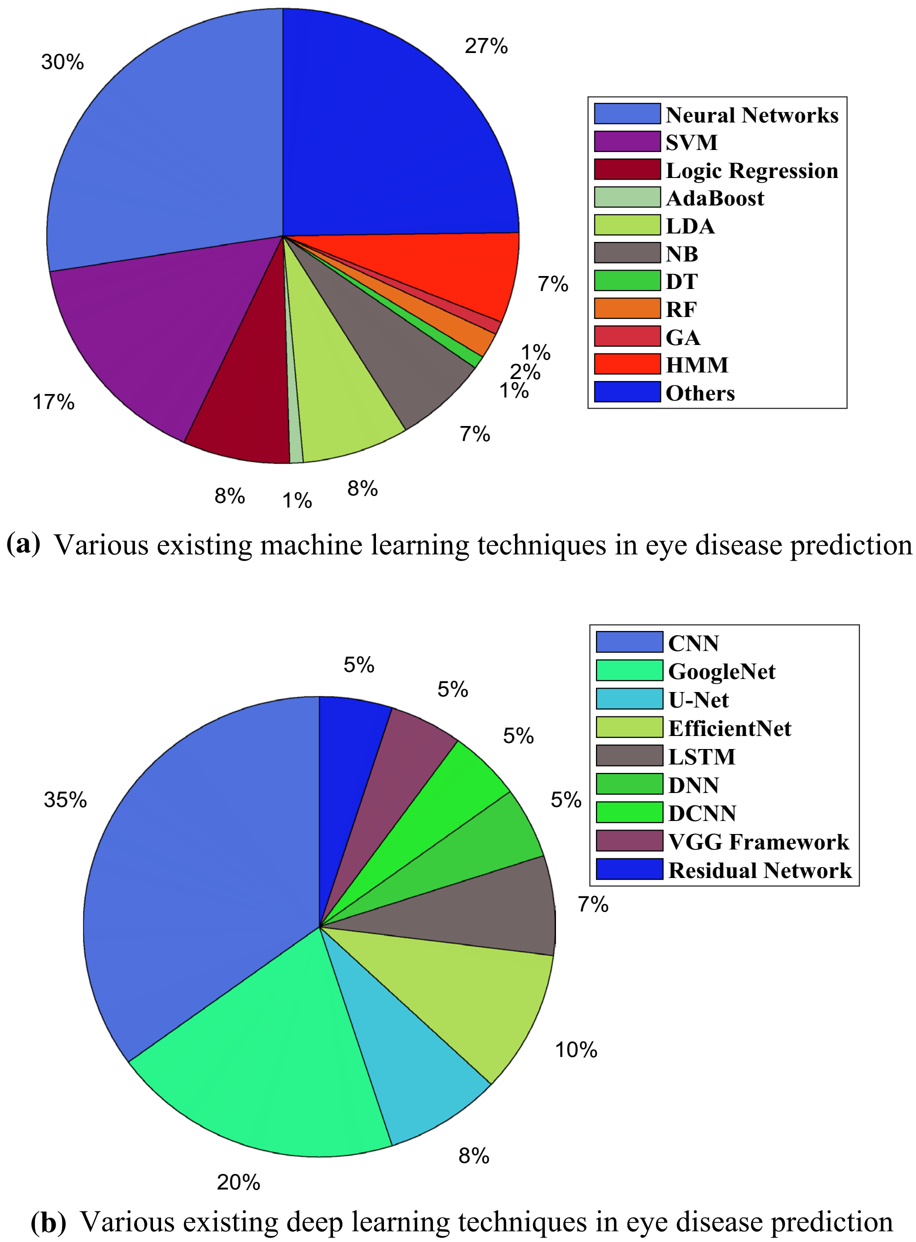

Fig. 1 **a** Various existing machine learning techniques in eye disease prediction. **b** Various existing deep learning techniques in eye disease prediction

recently attracted much attention. However, the study of medical images has evolved significantly with the advent of ML and DL schemes capable of extracting the necessary features to provide an accurate diagnosis. These systems require additional steps such as Pre-processing, selection of optimal network design and training. The automated fundus and OCT image categorization approach can detect a wider range of ophthalmic diseases. This article reviewed fundus images and OCT for the binary multi-class multi-label taxonomy of ophthalmic diseases. The different classification techniques of ML, like SVM, Kalman (KF), Principal Component Analysis (PCA) etc., are checked. Different pre-trained architectures like VGG-19, AlexNet, ResNet, Inception v3 etc., are reviewed in DL.

1.4 Key Contributions

The key contributions of deep learning technique analysis for the prediction of eye diseases, as outlined in a systematic review, can be summarized as follows:

- The systematic review provides a comprehensive overview of the current state of research on deep learning techniques for the prediction of eye diseases. It combines and analyses findings from a range of studies, thereby providing a complete understanding of the field.
- The review assesses the performance of various deep learning models, particularly CNNs, in predicting different eye diseases. It examines metrics such as accuracy,

Table 1 Diagnostic techniques and imaging techniques for the early diagnosis of various eye illnesses

ED	Techniques for imaging	Characteristics	Part of the eye
DR [49–51, 57–65]	Fundus photography, HRT, OCT	Haemorrhage, cotton wool, hard exudates, abnormal new vessels and microaneurysms	The eye's inside surface (posterior pole, macular, optic disc, and retina)
Cataract [55, 56, 79–81]	Ophthalmoscope, Fundus photography, MRI	Standard deviation, entropy, uniformity, and mean intensity	Cornea, iris, lens, sclera, and conjunctiva
Glaucoma [105–110]	Fundus photography, HRT, OCT	Par papillary atrophy, neural retinal rim, and cup-to-disc ratio	Macular thickness, tissue of the retinal nerve fibre layer, corneal thickness, retina
Multi-label [101–104] and Multi-class [93–100]	Fundus photography	Cataract, dilated pupil, corneal ulcer, pterygium, style, conjunctivitis, sub conjunctival	Blood vessels, sclera, Iris, Eye lid
DME [74–78]	HRT, OCT	Measurement of retinal thickness	Macular thickness, tissue of the retinal nerve fibre layer, corneal thickness, retina
AMD [111–116]	Fluorescein angiography, OCT, and fundus photography	Confluent drusen, large drusen, and pigment atrophy	The eye's inside surface (posterior pole, macular, optic disc, and retina)
Myopia [81, 82]	Fundus photography	Near objects are clear, and far objects are blurry	The region in front of the retina
Hypertension [45, 69, 85]	Fundus photography	Affects the tiny blood vessels in the eye	Blood vessels in the retina

sensitivity, specificity, and area under the curve (AUC) to evaluate the efficacy of these models.

- The review compares the performance of deep learning models with traditional machine learning algorithms and human experts. This highlights the benefits and potential of deep learning to outperform existing approaches to predicting eye diseases. The analysis focuses on specific eye diseases, such as diabetic retinopathy, glaucoma and age-related macular degeneration, among others. It examines how deep learning models have been applied to classify these diseases, providing insights into their effectiveness and potential clinical applications.
- The review evaluates the performance of deep learning models across different imaging modalities commonly used in ophthalmology, such as fundus photography, optical coherence tomography (OCT), and retinal scans.
- The review discusses the importance of high-quality, well-annotated datasets for training deep learning models in eye disease prediction. It explores the characteristics of existing datasets used in the studies, highlighting the need for diverse and representative data to enhance model generalization.
- The analysis acknowledges the challenges and limitations of current research, such as data variability, lack of standardized protocols, and interpretability issues of deep learning models. It also provides insights into potential avenues for future research and development in this field.

By offering a comprehensive evaluation and synthesis of existing research, the systematic review contributes to understanding deep learning techniques for predicting eye diseases. It supports the researchers in assessing the current state of the field and identifying opportunities for further advancements and improvements.

1.5 Problem Statement

The problem statement for the analysis of deep learning techniques for the prediction of eye diseases can be formulated as follows:

Eye diseases, such as diabetic retinopathy, age-related macular degeneration, cataract and glaucoma, pose significant challenges to healthcare professionals due to their complex nature and potential for irreversible vision loss. Early detection and accurate diagnosis are crucial for effective management and treatment of these conditions. However, traditional diagnostic methods often rely on subjective interpretations and can be time-consuming, leading to delayed interventions and suboptimal outcomes. Deep learning techniques have emerged as a promising approach to address these challenges. The DL models can potentially automate and improve the diagnostic process, enabling early detection and intervention.

Despite the potential benefits, the analysis of deep learning techniques for predicting eye diseases presents several key issues and gaps in the current research landscape. Comparative studies with existing diagnostic methods and assessment of the models' sensitivity, specificity, and predictive values are essential for determining their clinical utility and reliability. The availability of high-quality and diverse datasets is crucial for training and validating deep learning models. However, there may be limitations regarding the size, quality, and representativeness of available datasets, which can impact the generalizability and effectiveness of the models. Therefore, the analysis of deep learning techniques for the prediction of eye diseases aims to address these issues and gaps, providing a comprehensive understanding of the current state of the field, evaluating the performance of deep learning models, and identifying opportunities and challenges for their integration into eye disease prediction.

The following sections are then used to organize the systematic review. Section 2 provides the review methodology. In Sect. 3, automated diagnosis of eye disease using image processing is described. In Sect. 4, various categories of eye diseases are analyzed with a different machine, deep learning based approaches, and the systematic review is concluded in Sect. 5.

2 Review Methodology

This section reviews various deep learning techniques for different eye diseases. Different stages of the review are described in the following sections.

2.1 Systematic Review Stages

The stages of the systematic review depicted in Fig. 2 can be broken down into four categories: eligibility criteria, search method, data extraction, and research questions. The initial step is to conduct research queries, which in this case, focus on different methods of predicting eye diseases. The details for the specified research questions are extracted from multiple sources during the second stage, which is data extraction. The third step is the search strategy, specifying the terms used to locate the material. The eligibility criteria are the last part of the fourth stage and include the inclusion and exclusion conditions. The stages of a systematic review are shown in Fig. 2.

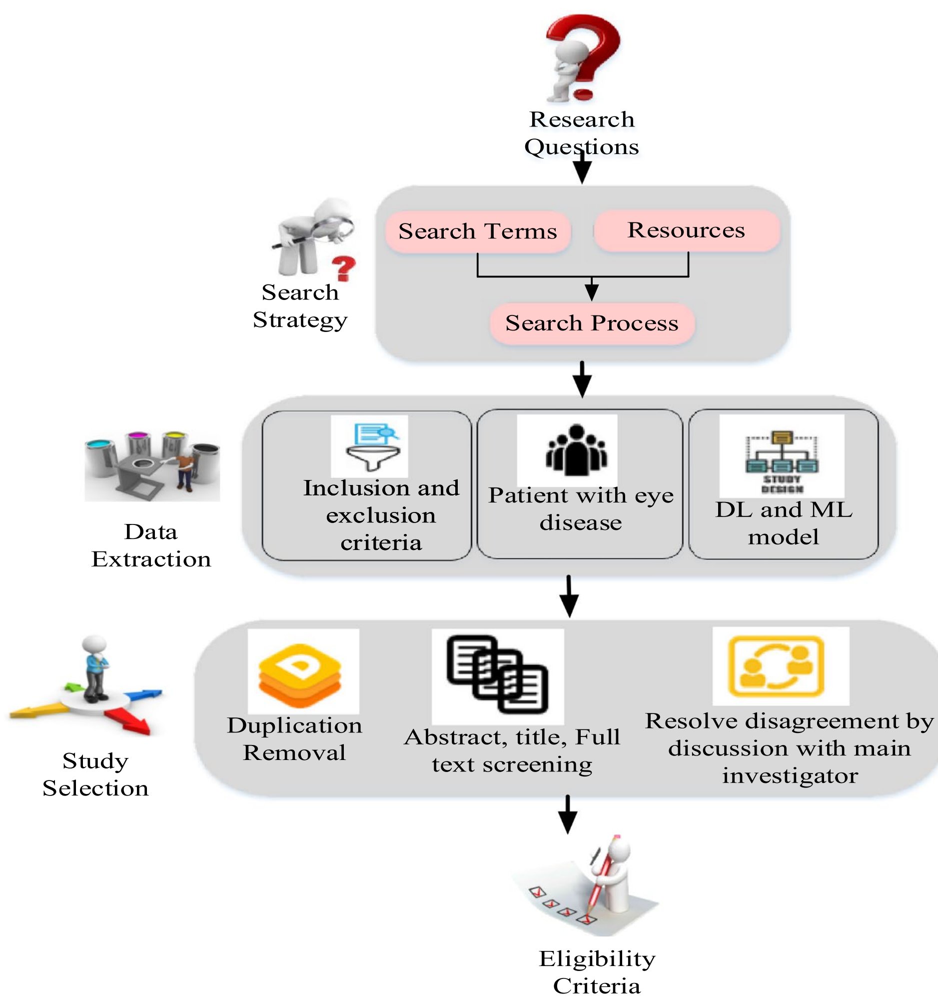

Fig. 2 Systematic review stages

2.2 Research Queries

Following are some research questions that are stated to begin the systematic review:

RQ1 What are the various eye diseases?

RQ2 What different modalities are used for eye disease screening?

RQ3 What is the purpose of eye disease prediction?

RQ4 What are the ML eye disease prediction techniques?

RQ5 What are the DL techniques used for eye disease prediction?

RQ6 What are the basic stages of eye disease prediction using the image processing technique?

RQ7 What are the most popularly used performance metrics to validate the performance of the proposed eye disease prediction techniques?

RQ8 What are the various challenges faced by the author in automatic eye disease prediction using deep learning techniques?

2.2.1 Datasets for Different Modalities

The different datasets available for automatic diabetic eye detection are listed in Table 2. The analysis of different datasets is shown in Fig. 3.

2.3 Search Strategy

The method is followed to originate with the search term as follows:

- The primary search terms are chosen based on the research questions.
- New phrases were created to replace important words like detection and prediction.
- Boolean operators are used to limit the search results (ANDs and ORs).
- The deep learning and ML related search terms are used in this review for Glaucoma, DR, cataract, and AMD detection.

2.4 Search Engines for Eye Disease Related Papers

In this stage, the final list of papers is examined to remove the data required to address the research questions. The authors searched for significant studies that used ML and DL to process eye images in order to perform this review. Before 2000, no relevant research was discovered. Therefore, the range of the chosen papers is only from 2000 to 2021. For the purpose of performing this review, the following online resources and digital libraries have been searched:

- Science Direct (https://www.sciencedirect.com)
- Elsevier (https://www.elsevier.com)
- IEEE Xplore (https://ieeexplore.ieee.org)
- Google Scholar (https://www.scholar.google.com)
- Springer (https://www.springer.com)
- ACM Digital library(https://dl.acm.org)
- PubMed (https://pubmed.ncbi.nlm.nih.gov)
- EMBASE (https://www.embase.com)

2.5 Study Selection

The study selection considered more than 300 papers based on the search criteria. Then, those publications are examined to ensure the review includes only those relevant to the topic. The filtration and selection processes are described below:

- All duplicate articles gathered from the various digital libraries should be deleted.
- Apply inclusion and exclusion criteria to prevent papers that are not relevant.
- Remove review articles from the collection of papers.
- Resolve disagreement through a discussion with the main investigator
- Follow the standards for quality evaluation, and only the standard articles are included to meet the requirements and to provide the most insightful answers to the research topics.

2.6 Eligibility Criteria

All research publications analyzed for predicting eye diseases met the next inclusion and exclusion criteria.

2.6.1 Inclusion Criteria

- The research papers completely examined the subject of image processing-based eye isease prediction.
- The research papers have clear core objectives.
- Papers using ML and DL methods to predict eye diseases are added.
- The only acceptable research papers are those written in English.

Table 2 Datasets description for automatic eye disease prediction

Dataset	Reference Number	Description
Kaggle 39 classes	[45, 69, 85]	The dataset comprised 1000 fundus images with 39 classes. The classes are normal, DR1, DR2, DR3, large optic cup, Tessellated fundus, possible Glaucoma, optic atrophy, dragged disc, disc bulge and elevation, severe hypertensive retinopathy, congenital disc irregularity, retinitis pigmentosa, Bietti crystalline dystrophy, peripheral retinal degeneration and break, myelinated nerve fiber, fundus neoplasm, BRVO, CRVO, silicon oil in eye, blur function without PDR, chorioretinal atrophy-coloboma, fibrosis, laser spots, preretinal haemorrhage, vessel tortuosity, massive hard exudates, yellow white spots flecks, cotton wool spots, vitreous particles
Adam Multi-class data EyePACS dataset	[46, 78]	The dataset provided by EyePACS. 35,126 images serve as training, while 53,576 serve as testing (a total of 88,702). The stages on these images are marked
RFMID-2021	[117]	The dataset comprised 3200 fundus images with 46 annotated conditions
IDRID	[35, 36]	The dataset comprised general diabetic retinopathy lesions and normal retinal annotations at pixel levels
PALM	[48]	It comprised 714 color fundus images with 5 grades of Myopic Maculopathy
Messidor	[34, 49, 65, 81, 85]	There are 1200 fundus images in the dataset. Three French ophthalmological branches provided the images. 800 of the 1200 total images feature dilated pupils, while just 400 do not. DR phases are indicated on images
Messidor-2	[42, 65]	There are 1748 fundus images in the dataset. The camera utilized had a 45-degree field of view and was a Topcon TRC NW6 nonmydriatic
STARE	[43, 64]	400 fundus images make up the dataset. With a 35-degree field of vision, the Topcon TRV-50 was used to capture the images
E-optha	[49, 50]	The dataset includes 268 photos without a lesion, 148 images with microaneurysms, and 47 images with exudates
RIGA	[35]	The dataset has three sources: Magrabi Eye Center (It contains 95 original images annotated by six dissimilar ophthalmologists of 665 total images)
REFUGEE	[53]	The dataset consists of a total of 1200 annotated fundus images. The resolution of the considered images is 2124×2056 pixels
ORIGA	[53, 55, 76]	A quantitative, impartial scoring technique was proposed based on the cup-to-disc ratio and cup segmentation, as well as the optic disc. The Singapore Eye Research Institute's qualified experts have annotated 650 retinal images in ORIGA. A large number of image indications that are crucial for the diagnosis of glaucoma were labelled
ADAM AMD	[34]	Automatic discovery challenge on age connected macular degeneration dataset (ADAM AMD) comprised various fundus lesion images of AMD patients
Drishti-GS	[65]	A total of 101 images are included in the dataset. 50 training examples and 51 test examples were selected from the images. Four ophthalmologists marked the photographs after they were taken at Aravind Eye Hospital
ODIR-2019	[66, 67]	With 207 training classes, 58 on-site test cases and 30 off-site test cases, this dataset includes eight different forms of eye diseases
RIM-ONE	[76, 84]	Dataset information: I118 (i) r1 Non- glaucoma images 118 and 40 glaucomas; (ii) r2 225 Non-glaucoma images and 200 glaucomas; as well as (iii) r3 85 Non- glaucoma images and 74 glaucoma
CLEOPATRA	[62]	In the United Kingdom, fifteen ophthalmic centres participated in the three-phase, parallel, and single clinical experiment called CLEOPATRA

- The current research papers are used for eye disease prediction.

2.6.2 Exclusion Criteria

- Duplicate publications.
- Studies that weren't fully published in the full text.
- Letters, comments, case studies, seminar reports, and review papers.
- Exclude any articles that use ML and DL but are unrelated to the prediction of eye diseases.
- Remove the articles published before 2000
- Studies that were not published in English

The PRISMA model of the search processing based on the inclusion and exclusion criteria is given in Fig. 4.

The PRISMA guidelines were followed in this systematic review, as depicted in Fig. 4. Few review articles have discussed using different methods to create an eye disease prediction system. Consequently, the main objective of the proposed systematic review is to organize all recent research publications dealing with ML and DL based eye disease

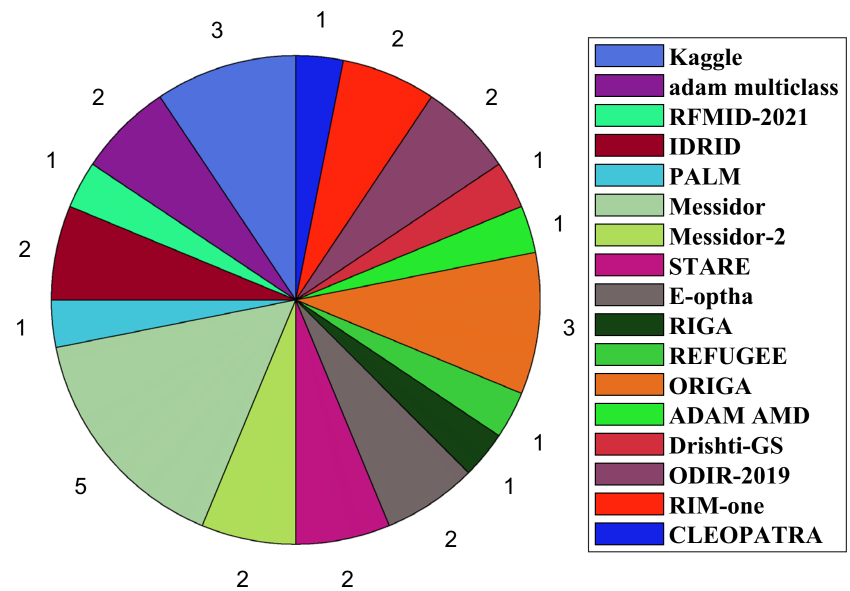

Fig. 3 Analysis of different datasets

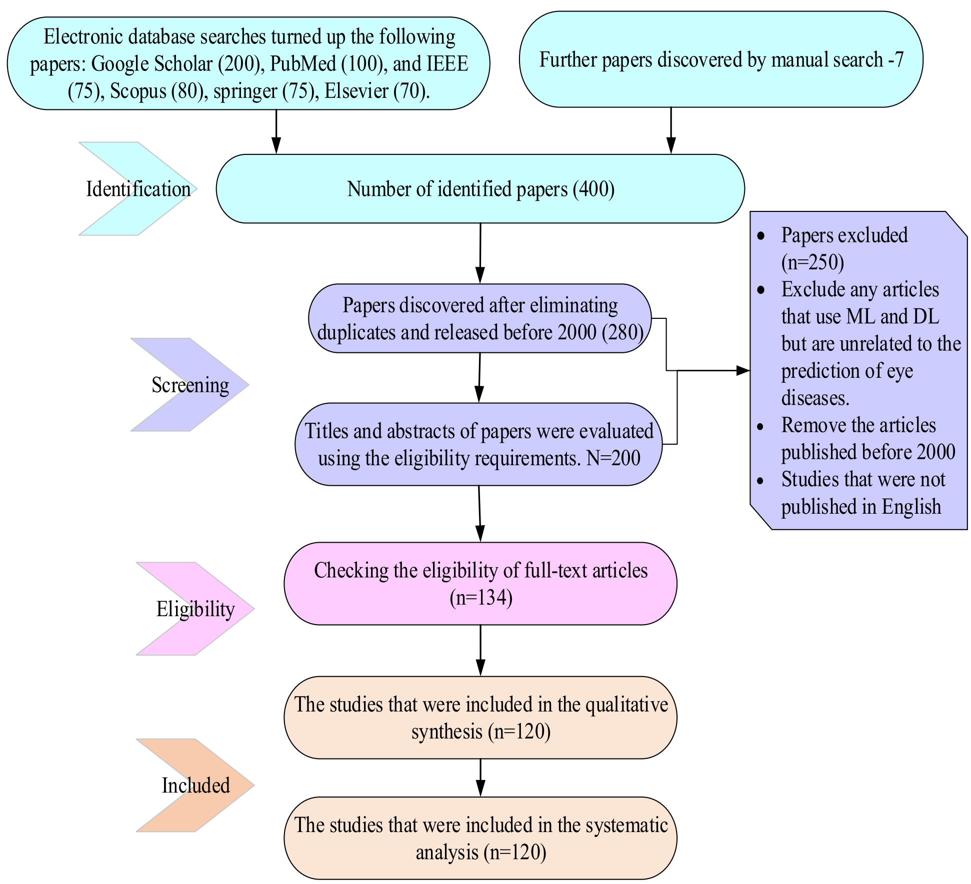

Fig. 4 PRISMA model of the search processing based on the inclusion and exclusion criteria

diagnosis and prediction systems to provide a clear idea of potential medical breakthroughs. The number of papers examined from 2000 to 2023 is shown in Fig. 5.

The proposed systematic review provides a comprehensive introduction to the basics of eye diseases and the different types of medical imaging modalities.

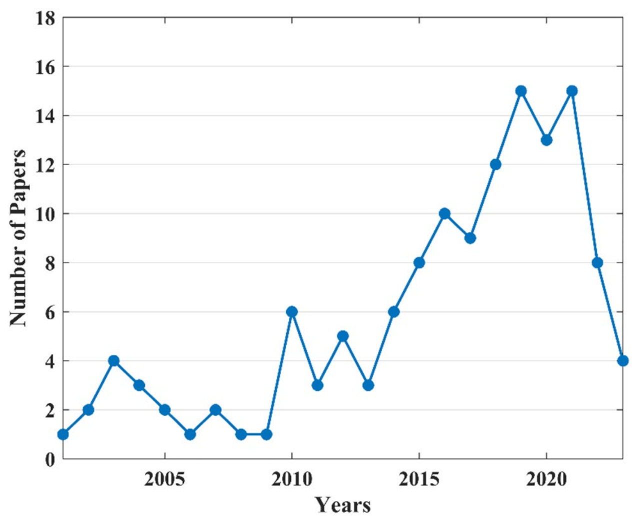

Fig. 5 Number of papers reviewed from 2000 to 2023

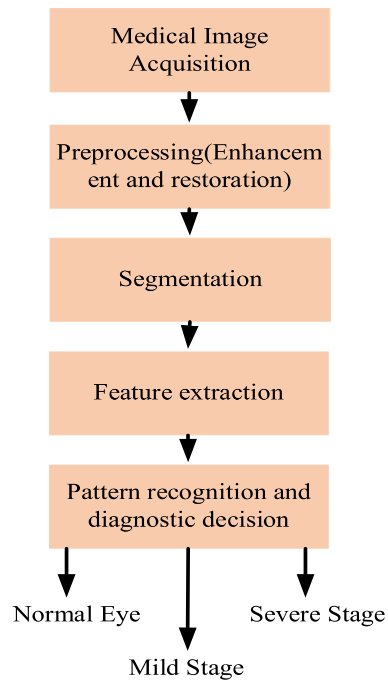

Fig. 6 IP technique for eye disease prediction

3 Automated Diagnosis of Eye Disease Using Image Processing

Image processing (IP) based approaches are currently receiving a lot of attention due to their ability to automatically detect and diagnose various eye diseases. The phases of the IP-based diagnostic framework include eye image acquisition, pre-processing, segmentation of the ROI, feature selection, and eye disease classification. Figure 6 shows the block design of an IP-based system for the automatic detection of eye diseases.

The green channel in the RGB colour space contrasts more than the additional channels. The green channel in the RGB color space has more contrast than the additional channels. The majority of image pre-processing methods use green channel extraction. Compared to the blue and red channels, the green channel image provides more data. The eye images are taken according to the need for various imaging methods, such as an ultrasound image for a detached retina, a fundus image for Glaucoma and DR, and an OCT image for macular degeneration. Ophthalmologists often use MRI and HRI images to diagnose eye diseases. Compared to other imaging methods, HRI and MRI imaging are more expensive. Therefore, these imaging approaches in IP-based systems for automated detection and diagnosis are rare.

Pre-processing aims to improve contrast and reduce impulse noise in these images. Since these images were taken with multiple imaging modalities under different conditions, salt-and-pepper noise and uneven lighting can be introduced. The need for improvement stems from the adverse effects of unevenly poor contrast, noise on collected images, and lighting. The presence of noise in the retinal image increases the likelihood of misidentifying lesions. Therefore, pre-processing is essential for any recognition system. Segmentation is performed after pre-processing to extract the region of interest (ROI) from the pre-processed image, which provides crucial information about anomalies. The segmented image is used to extract a number of features. These properties help the training parameters of a classification model [46–48]. Automated disease diagnosis is achieved using computer vision, pattern recognition and artificial intelligence (AI). A variety of classification models are available for grading and diagnosing eye diseases, including Radial Basis Function Neural Net (RBFNN), CNN, Random Forest (RF), Softmax, Artificial Neural Network (ANN), SVM, and Long Short Term Memory (LSTM), are commonly used. The collected feature parameters are used for training and testing.

4 Eye Disease Prediction

In the medical industry, automated screening and diagnosis save time, reduce the possibility of misdiagnosis and lowers labor and financial costs for physicians. Automation is progressing rapidly due to the feasibility and development of DL methods that allow machines to understand complicated aspects of medical data. In ophthalmology, significant attempts have been made to study retinal images and provide analytical frameworks for identifying retinopathy and assessing its severity [136]. The various research papers on DR, Glaucoma, AMD, DME and cataract prediction based on ML and DL are reviewed.

4.1 ML Techniques for DR Prediction

Using Deep Visual Features (DVF), Abbas et al. [49] created an SVM classifier to determine the severity of DR in fundus images (DVFs). Gradient Location Orientation Histogram (GLOH) and Dense Color Scale Invariant Feature Transform (DColor-SIFT) were used for feature extraction. DR fundus images are classified into five severity categories: moderate, no DR, severe NPDR, mild, and PDR were constructed using an SVM classifier. In terms of efficiency and timing, the overall performance of the used algorithm was evaluated. For all DR severities, an average area under the receiver operating curve (AUC) of 0.924, a sensitivity (SE) of 92.18%, and a specificity (SP) of 94.50% were obtained, indicating a superior value to previous approaches. The main disadvantage of this method was that only one image was used for classification, and at least two fundus images were needed to identify the four quadrants required to identify severe retinopathy.

To support patients in the early detection of diabetic retinopathy, Enrique et al. [50] an innovative diagnosis with digital processing and computer support of retinal images was developed. The main goal is to automatically classify the NPDR grade of each retinal image. To do this, an initial stage of image processing separates hard exudates, microaneurysms, and blood vessels to derive features that SVM can use to determine the degree of retinopathy in each retina image. Here, a predictive capacity (PC) of 94% and a maximum sensitivity of 95% were found. The determination of soft exudates was not possible with this method.

Sumandeep and Diljith [51] created a method for classifying and diagnosing DR using SVM and curvelet transforms. First, an empirical transformation is used to enhance retinal images. Canny-edge detection removes the eyeball from an image of the retinal fundus. The errors in the images are then found using morphological methods. Finally, the SVM categorizes images as normal, proliferative, or non-proliferative. A comparison table for predicting DR using ML is presented in Table 3.

4.2 ML Techniques for Glaucoma Prediction

Eswari and Balamurali [52] introduced a machine learning model, an intelligent prediction system to predict glaucoma. The Bayesian optimization support vector machine (BOSVM) is integrated into a local real-time dataset of diabetics in this introduced system, and it accurately predicts glaucoma with 96.6%, 0.83 in the AUC for the training set, and 97.3% accuracy with 0.943, 0.951, and 0.943, 0.951 of sensitivity and specificity. This model will soon be used with a sizable real-time dataset and numerous classifiers instead of binary classifiers.

Supriya et al. [53] used a comprehensible, discrete state space model to model and predict longitudinal glaucoma data. A CT-HMM (continuous-time hidden Markov model), based on a typical order of temporal data taken during appointments, depicts the continuous variation in functional and structural measures. Comparing our results to earlier work using the average RNFL thickness, a mean absolute error (MAE) reduction of 74% is attained. This research will be helpful for precisely predicting the geographic distribution and pace of tissue ageing. Correct intervention depending on a more precise prognosis may help to advance glaucoma clinical care.

The Kalman filter algorithm (KF) was developed by Gian-Gabrial et al. [54] and used in a method for predicting normal tension glaucoma (NTG). KF is a potential method that can be used to create tailored predictions and learn the course of disease in groups of glaucoma patients. The RSME value and the prediction error distribution of the introduced

Table 3 Comparison table for prediction of DR using ML

Author and reference	ED	Technique	Dataset	Different classes	Performance	Drawback
Abbas et al. [49]	DR	SVM	Foveal Avascular Zone Messidor, DIARETDB1, Hospital Universitario Puerta del Mar, HUPM, Cádiz, Spain	Mild, Moderate, and Severe	AUC-0.924 Sp-94.50% SE-92.18%	It needed at least two fundus images to identify the four quadrants required for diagnosing severe retinopathy when just one image was utilized for categorization
Enrique et al. [50]	DR	SVM	Messidor database	Mild, Moderate, and Severe	SE-95%, PC-94%	Soft exudates determination was not possible with this method
Sumandeep and Diljith [51]	DR	SVM	Retinal fundus image	Normal, proliferative or non-proliferative	SE-96.77%, SP-100%, and Accuracy-97.78%	The accuracy depends on the PSNR value

method are evaluated. If the accuracy of our predictions can be directly extrapolated to patients with NTG living in other countries, further studies are needed to make this determination. The comparison of glaucoma prediction using ML is presented in Table 4.

4.3 ML Techniques for Cataract Prediction

For the categorization and grading of cataracts using fundus images, Guo et al. [55] examined a CAD healthcare system. The system comprises cataract categorization and grading, feature extraction, and fundus image pre-processing. The fovea and blood vessels in the organs were more clearly visible in the non-cataract fundus image than in the cataract fundus image. The feature extraction method uses discrete cosine transforms (DCT) and discrete wavelet transforms (DWT). The wavelet transformation coefficient data matrix was graded using principle component analysis (PCA). The two-class classification and the cataract grading have classification rates of 90.9% and 77.1%, respectively.

Zheng et al. [56] presented a classification system for cataracts based on fundus images. To identify the cataract feature, a 2-D DFT was used for a fundus picture. PCA was then used to minimize the dimension. Four classifications have been established using linear discriminant analysis (LDA). The classifier is promoted using the Ada-Boost method. The classification accuracy for the suggested method is correspondingly 95.22% for two classes and 81.52% for four classes. A comparison of cataract prediction using ML is given in Table 5.

The fields of image classification, segmentation, and enhancement approaches have seen substantial advancements in ML algorithms. Despite initially producing improved results, ML algorithms could not pick up

Table 4 Comparison of glaucoma prediction using ML

Author and reference	ED	Technique	Dataset	Different classes	Performance	Drawback
Eswari and Balamurali. [52]	Glaucoma	BOSVM	Health Report of diabetic patients	Chance and no chance	Accuracy-96.6% AUC-0.83	This model will soon be used with a sizable real-time dataset and numerous classifiers instead of binary classifiers
Supriya et al. [53]	Glaucoma	CT-HMM	Eye Center at the Univ. of Pittsburgh Medical Center	Multi-class	Error reduction of 74%	Correct intervention based on a more precise prognosis may help to advance glaucoma clinical care
Gian- Gabrial et al. [54]	Glaucoma	KF algorithm	Clinical image	NTG prediction	RSME and prediction error	If the precision of our forecasts can be directly extrapolated to patients with NTG living in other nations, more study is required to make that determination

Table 5 Comparison of cataract prediction using ML

Author and reference	ED	Technique	Dataset	Different classes	Drawback
Guo et al. [55]	Cataract	DWT, DCT, PCA	Retinal fundus image	Cataract and Non-cataract type	Clinical application is not possible with this method
Zheng et al. [56]	Cataract	DCT, PCA	Fundus image dataset	Normal, mild, moderate, severe	In the early stage, prediction is not possible

additional features as the dataset increased. DL techniques produced more features as the amount of data increased, while neural networks, a subset of ML algorithms, performed remarkably well with the data. DL techniques have become the benchmark for all image classification tasks. The number of papers reviewed for various eye diseases is depicted in Fig. 7.

4.4 DL Techniques for Prediction of DR

A lot of research has been done to automatically identify DR using DL. To implement an automated DR detection method on a publicly available data set by including DL, Abramoff et al. [57] used a CNN approach dependent on AlexNet and Random Forests (RF) classifiers. The attained performance using the Messidor-2 dataset were AUC (98.0%), sensitivity (96.8%), predictive negative value (99.0%), and specificity (87.0%).

Using the STARE dataset, the binary categorization for 10 samples was carried out to detect retinal illnesses by Choi et al. [58]. In this instance, DL used a CNN for fundus image analysis in a situation with many illness categories. Here, the Random Forests classifier was combined with the VGG-19 architecture and stochastic gradient descent (SGD) optimizer. The method obtained the AUC, specificity, and sensitivity of 90.3%, 85.5%, and 80.3%, respectively.

The VGGNet architecture was used by Ting et al. [59] to categorize DR and many illnesses, such as AMD glaucoma. Datasets were gathered from the Singapore Screening for DR in the United States (SIDRP) between 2010 and 2013 with specificity (91.6%) and AUC (93%), and sensitivity (90.5%). The proposed framework succeeded for glaucoma with 87.2% specificity, 96.4% sensitivity, and AUC of 94.2%. Finally, the developed framework managed to achieve 92% sensitivity for the referable DME.

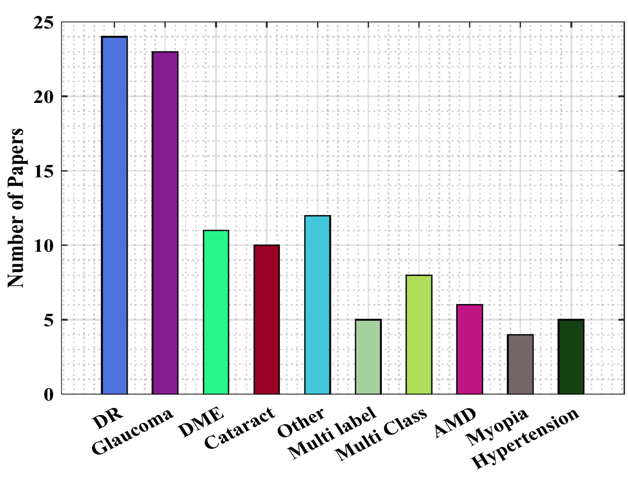

Fig. 7 Number of papers reviewed for various eye diseases

Gondal et al. [60] suggested a DL approach that emphasizes regions of interest in retinal images that show signs of DR aid in making a clinical diagnosis. The award-winning CNN architecture o_ O solution was used here since good class-specific characteristics and high classification accuracy are crucial. DR lesions like microaneurysms, soft exudates, haemorrhages, and red spots are found using the o_O solution. The global average pooling layer was used instead of the dense layer. On the DIARETDB1 dataset, the proposed framework attained an AUC of 95.4%.

Inceptionv3 was utilized by Gulshan et al. [61] to discover DR on the Kaggle dataset and datasets gathered from three major hospitals in India. The obtained specificity was 98.2% with a sensitivity of 90.1% for an advanced level with relation to DR. Additional investigation is required to determine if the use of this technique is feasible in a clinical setting and to assess whether the application of the algorithm would lead to better treatment and better outcomes than the present ophthalmologic analysis.

To complete a DR classification framework employing OCTA and OCT, a CNN-based technique is introduced by Gao et al. [62]. A dense plus continuous connected neural network (DcardNet) with adaptive rate dropout was constructed for DR classification. The overall classification accuracies of 3 levels were 71.0%, 85.0%, and 95.7%, correspondingly in the DcardNet-36 and ResNet-18 datasets.

Daanouni et al. [63] suggested a simple modified CNN model for the OCT-based diagnosis of DR. Here, a custom CNN was retrained using the pre-trained CNN models, namely MobileNet with a transfer learning technique, for reliable OCT classification. The achieved metrics for the suggested architecture were accuracy, precision as well as recall of 80%, 85% and 80.5%, respectively.

Exudates were found using a modified U-Net by Li et al. [64]. For the purpose of segmenting neuronal membranes, U-Net was created. Unpooling layers were used instead of U-Nets de-convolutional layers in the updated architecture. AUC values of 0.98, 0.96, 0.94, and 0.91 were obtained for the trained model when it was verified on its own labelled dataset and three publicly accessible databases.

Using the LeNet architecture, Perdomo et al. [65] distinguished between standard DR images and images with exudates. The authors obtained a sensitivity of 99.8%, an accuracy of 99.6%, and a specificity of 99.6% using the e-ophtha dataset. A modified GoogLeNet was used by Takahashi et al. [66] to identify the different stages of DR. By removing the five accuracy layers from Google Net and reducing the sample size to four, and obtained a Kappa value of 74% and an Accuracy of 81%.

4.5 DL Techniques for Prediction of Hypertension

When analyzing spectral domain OCT (SD-OCT) to identify among eyes with and without glaucomatous VF damage (GVFD) and to predict the degree of GFVD, Mark et al. [67] developed a DL system using ResNet50 and Image Net. To compare DL models with mean RNFL thickness for GVFD recognition, different metrics such as AUC, sensitivity, and specificity were employed. Regarding recruitment/collection procedures, race, age, or certain other unidentified confounding factors, the study population was gathered as part of DIGS and ADAGES. The models may discover structure–function relationships that are particular to these data. A Kaggle subcategory of the Kermany dataset was used by Bhowmik et al. [85] to expedite training. In order to use AI to treat ageing and macular degeneration, this data gathering trains the intensive learning algorithms on NORMAL, CNV, and DRUSEN images.

4.6 DL Techniques for Prediction of Glaucoma

Several investigations have been carried out to automatically identify glaucoma using DL. Using fundus colour images is a valuable technique of DCNN for identifying eyes with suspected Glaucoma or Glaucoma. 3312 images were used by Phan et al. [68] for the DCNN analysis. These images included 2687 non-glaucoma eyes and 369 images of glaucoma eyes. 90% of the AUC was attained.

Muhammad et al. [69] demonstrated the degree to which a single wide-field OCT technique and a hybrid DL method (HDLM) between eyes were previously categorized as either moderate glaucoma or healthy suspicions. Depending on the feature vector of CNN, an RF classifier was built here to divide patients into glaucomatous and healthy groups. Depending on the input map, the accuracy of the HDLM varied from 63.7 to 93.1%.

According to Sudhan et al. [70], a persistent transfer learning model and a U-Net based architecture on the DL algorithm were used for the OC segmentation. The characteristics for glaucoma prediction are extracted using the DenseNet-201 deep CNN. The model was assessed using precision, specificity, accuracy, recall, and F-measure metrics. In training and testing, the developed model has an accuracy of 96.90% and 98.82%, respectively. In this study, the ORIGA dataset was utilized for assessment.

Samuel et al. [71] developed a DL technique utilizing a generalized variational auto-encoder (VAE) to enhance the assessment of rates of progression as well as predict the outlines of VF loss in glaucoma. Using patient-level randomization, the VAE was taught utilizing a 90% sample of data. Rates of advancement and predictions were created utilizing the remaining 10%, and related to point-wise regression forecasts and SAP mean deviation (MD) rates, respectively.

Shotaro et al. [72] planned to train a CNN with OCT pictures and adjust the values with the 24–2 Humphrey Field Analyzer (HFA) test to create a model to predict VF in the centre 10 degrees in glaucoma patients. In addition, the HFA 24–2 test, HFA 10–2 test, and an OCT examination of all eyes were performed on the eyes with the testing dataset. The CNN model's MAE was between 9.4 and 9.5 dB. When the results were adjusted using the HFA 24–2 test, these values decreased to an average of 5.5 dB.

Juan et al. [73] utilized various CNN techniques to demonstrate the impact on the performance of pertinent elements such as data set size, architecture, and freshly specified architectures versus transfer learning. Additionally, the effectiveness of the CNN-based system was evaluated here compared to human evaluators, and the impact of integrating patient clinical history data and images was also examined. Compared to the various existing studies, VGG19 accomplished an AUC of 0.94.

Baidaa et al. [118] evaluated whether it was possible to use DL to produce a system aimed at automatic feature learning for glaucoma detection in coloured images of the retinal fundus. A fully automated system built on CNN was intended to differentiate the class of normal and glaucomatous patterns. To determine whether the images are abnormal or normal, CNN automatically extracts the attributes from unprocessed images and provides them to the SVM classifier. Compared to the state-of-the-art, 88.2% accuracy, 90.8% specificity, and 85% sensitivity are determined at a much lesser computational cost.

A CNN for feature learning has been used by Xiangyu et al. [119] using automatic feature learning for glaucoma detection (ALADDIN). A contextualizing training technique that is used to learn the intricate details of glaucoma is also developed. The findings show that the AUC for glaucoma detection in the receiver operating characteristic curve (ROC) is much higher in the two databases, at 0.838 and 0.898, compared to existing techniques. The investigation is broadened with the deep learning architecture built on C-CNN to include the identification of different eye illnesses.

Sertan and Ali. [120] introduced a generic DL model for fundus images-based detection of glaucoma. ResNet models and GoogLeNet models are utilized to categorize glaucoma. ResNet, GoogLeNet, and ResNet-152 are the three deep learning architectures used by the model. According to the discoveries, the model was 80% of the time superior to the past work in literature.

An effective segmentation technique for the segmentation of OC, as well as OD, was developed by Shuang et al. [121] using a modified U-Net architecture and ResNet-34 model mixed with conventional U-Net decoding layers. The experts' performance for OC or OD segmentation and CDR estimation on a reserved RIGA dataset was comparable to that of the model, having an average dice value of 97.31% and 87.61% for disc and cup segmentation, respectively. It was trained on the recently made available RIGA dataset. The algorithm will soon undergo additional testing in a clinical environment to confirm its effectiveness and robustness.

Mark et al. [122] compared the effectiveness of developing numerous deep learning algorithms on different datasets. These models were created using largely comparable deep learning model construction techniques, both employing ResNet30 architectures as well as horizontal flipping to enhance the data. However, there were minor changes in layer depth and training hyperparameters. High accuracy in glaucoma detection can be attained across various datasets and effective training methods. The difference in glaucoma explanations and labelling amongst the various datasets, particularly among the MCRH/Iinan/Hiroshima, ACRIMA, and DIGS/ADAGES datasets, is one of the weaknesses of the study.

Yidong et al. [123] created an HMM model for diagnosing glaucoma; both automatic hidden features learning and domain knowledge are used. The usefulness of the suggested model is assessed using actual datasets and obtains greater sensitivity, specificity, and accuracy (0.9090, 0.9233, and 0.9151, correspondingly) than the most recent models. First, the experimental data set is expanded to build a more complex model, and the performance can be increased even further. Second, an FCN capable of simultaneously segmenting the optic disc, cup, and PPA is constructed.

WangMin et al. [124] introduced a clinically interpretable deep learning model to accomplish accurate automated glaucoma detection and give a clearer analysis by emphasizing the various regions to support the diagnosis. ConvNet architecture with clinical interpretation (EAMNet) based on CNN not only obtains a precise diagnosis of glaucoma but also gives a clearer interpretation by emphasizing various regions the network has identified. With an AUC of 0.88, this approach for diagnosing glaucoma reaches state-of-the-art accuracy. To address the weakly-supervised evidence-based clear cup segmentation, further research must be done to create a more empirical model.

Marriam et al. [125] provided a model, EfficientDet-D0 with EfficientNet-B0, for extracting key points that would improve the performance of glaucoma recognition whereas reducing the model's training and execution times. In terms of recall, accuracy, AUC, precision, and time were used for the performance evaluation. Certain feature section techniques on deep learning simulations can be used in the new developments. Moreover, the research assess can be extended to other different eye conditions.

Qaisar. [126] presented a CNN method for the recognition of glaucoma. A softmax regression classifier was used with CNN to detect whether it was glaucoma affected eye or a normal eye. In the performance evaluation, the statistical metrics obtained as specificity, accuracy, and precision were 98.01%, 84.50%, and 84.50%, correspondingly. Large-scale glaucoma datasets can be used to estimate the Glaucoma-Deep system's practical usability.

Arkaja et al. [127] offered a CNN approach for detecting glaucoma. The results of our experiment serve as the AUC values. As mentioned before, an ophthalmologist needs a clear report to check glaucoma disease. Therefore, developing a system that can effectively diagnose this condition is imperative.

Allan et al. [128] suggested a system for automatically classifying images of the fundus to detect glaucoma. Initially, a sliding-window strategy coupled with GoogleNet was utilized. The results showed that the network was accurate even with low-quality images generated by the data augmentation technique or discovered in various databases. The images in the databases can be pre-processed for upcoming work, and the number of test image databases can be increased.

Deepa et al. [129] introduced the UNet-SNet two-stage DL framework for recognizing glaucoma. Tested on the Drishti-GS1, ACRIMA, and RIMONEv1 datasets, the classifier achieved accuracy rates of 99.86%, 97.05%, and 100%, respectively. The glaucoma assessments may use various methods, including stereo imaging, optical coherence tomography, visual field testing, and scanning laser polarimetry.

Glaucomatous structural change was discovered by Jinho et al. [130] using a DL method on the basis of spectral-domain optical coherence tomography (SD-OCT). NASNet (neural architectures search network) created the DL model. With a sensitivity of 94.7% and a specificity of 100.0%, this DL system achieved an AUC of 0.990. The research has some major limitations, like dataset insufficiency.

Andres et al. [131] used five distinct ImageNet-trained models for autonomous glaucoma assessment utilizing fundus pictures (VGG19, ResNet50, VGG16, InceptionV3, and Xception). To the best of the authors' knowledge, the AUC, specificity, and sensitivity were validated from the suggested methodology utilizing both the cross-validation procedure and the cross-testing authentication. To expand the number of training images for CNNs, research on user generated images to train CNNs might be quite successful.

Juan et al. [132] used several developed CNN methods to improve the output performance. In terms of AUC, specificity, and sensitivity, the five studied architecture standards, such as ResNet50, CNN, DENet, VGG19, and GoogLeNet, offered good performance result ratios. To validate this line of research, additional experiments using more data and different architectural techniques should be created and evaluated.

The segmentation procedure for the glaucoma detection used by H.N Veena et al. [133] to generate a reliable outcome, a DL design with an improved two CNN model for OC and OD individually, was introduced. The DRISHTI-GS database is utilized for the training and testing process. Here, the existing CNN model attained OC segmentation and OD segmentation accuracy of 97% and 98%, respectively. This model can be applied to numerous medical image segmentation applications.

Huazhu et al. [134] developed a DL approach to gathering more data on the image and quickly identifying glaucoma from the fundus picture. The local optic disc area and the deep hierarchical context of the global fundus image are combined, and an innovative Disc-aware Ensemble Network (DENet) for automated glaucoma screening is recommended. The performance evaluation was done according to the statistical measures of AUC, sensitivity, specificity and accuracy. The main drawback of this study has diminished the performance according to the SINDI dataset. Further, an MLP (Multi-layer perceptron) based ANN was developed in [135] for glaucoma detection, which utilizes GLCM (Gray Level Co-occurrence Matrix) for feature extraction. It efficiently classifies the fundus images and achieves 93.4% accuracy. The comparison analysis of eye disease prediction using DL techniques is specified in Table 6.

4.7 DL Techniques for Prediction of DME

Sahlsten et al. [74] introduced a framework for the binary categorization of DME into Referable DME and Non-Referable DME. The attained performance of DME prediction was specificity (97.4%), sensitivity (89.6%), and AUC (98.7%). The MESSIDOR database of 1200 images was used by Al-Bander et al. [75] to propose a CNN system to rate the severity of DME utilizing fundus images. Their results showed a specificity of 96.5%, sensitivity of 74.7%, and accuracy of 88.8%.

Using the DRiDB dataset, Prentavsic et al. [76] presented a unique supervised CNN-dependent exudate detection algorithm. The developed CNN framework comprised 10 layers with convolutional and max-pooling layers. The introduced scheme attained a 78% sensitivity, 78% forward stochastic correlation (FSc) and 78% positive predictive value (PPV). The image dataset from CLEOPATRA was used by Tan et al. [77]. The obtained sensitivity and specificity values were 87.58% and 98.73%, respectively. To detect AMD as well as DME, Kaymak et al. [78] employed the Alexnet model on the Kermany dataset.

4.8 DL Techniques for Prediction of Cataracts

T. Pratap et al. [79] concentrated on cataract diagnosis utilizing fundus retinal images (200 photos per category) and accomplished an accuracy of 92.91% using DL CNN, SVM, and a 4-stage classification method (severe cataract, moderate, mild, normal). The discovery of diabetic eye disease in fundus images was introduced by Sarki et al. [80] using the DL algorithm Vgg16 on the Messidor, DRISHTI-GS, messidor2 database 101 retinal images (70 lesions, 31 normal images), and datasets of retina having 100 cataract images. The introduced scheme achieved the mild multi-class category with an accuracy of 85.95%.

4.9 DL Techniques for Prediction of Myopathy

Ram et al. [81] examined CNN to categorize fundus retinal pictures using DL algorithms. 10,000 pictures from 5000 people with multiple diseases were collected, together with multi-label data for four groups of diseases (238 AMD, 1624 Normal, 308 Cataracts, and 243 Myopia). The developed deep CNN framework can accurately predict myopathy disease.

To directly diagnose many eye disorders, Wang et al. [82] suggested a multi-label classification ensemble model (InceptionResNetV2, EfficientNetB3). On ODIR-19 fundus images, 10,000 images were taken from both eyes of 5000 patients. The eight classes in ODIR-19 dataset were 149 Hypertension, 238 AMD, 243 Myopia, 1620 DR, 1624 Normal, 305 Glaucoma, 308 Cataract, and other classes 1393 images.

Rubina Sarki et al. [138] introduced a CNN framework for a multi-class categorization of diabetic eye disease. At first, the input images were collected from the fundus image dataset and pre-processed to eliminate the noise present in the images. Finally, the CNN framework was used for the categorization of images into multiple classes of eye diseases. The introduced model achieved accuracy 81.33% accuracy. However, the performance can be enhanced further using advanced schemes.

Saif Hameed Abood et al. [139] introduced a hybrid retinal image improvement scheme for detecting diabetic retinopathy using deep learning based approaches. Here, two stages were considered for eye disease prediction. The first stage was cropping to eliminate the unimportant content. Then, gaussian filtering was applied to reduce the noises and enhances the contrast of the images. The performance of the introduced scheme can be enhanced further with different colored medical patterns. Most of the fundus images were obtained from various contrasts and resolutions.

Muhammad Mohsin Butt et al. [140] developed a hybrid deep learning framework for identifying diabetic retinopathy diseases. Here, a transfer learning based framework

Table 6 Comparison of various eye disease predictions using DL

Author	Technique	Objective	Performance	Merits	Demerits/Research Gap
Baidaa et al. [118]	CNN	• Examined the feasibility of developing a system that automatically learns features to identify glaucoma •Deep learning technique applied to coloured retinal fundus images	Accuracy, Specificity Sensitivity	Lower computational cost	There is a need for more effective data augmentation and data sampling techniques to improve the effectiveness
Xiangyu et al. [119]	CNN	• A CNN for feature learning, which uses ALADDIN for the detection of glaucoma	AUC	Reduced over fitting problem	The investigation of deep learning architecture built on C-CNN can be extended to include the identification of different eye illnesses
Sertan and Ali. [120]	ResNet Google Net ResNet-152	A generic DL model was introduced for fundus image based glaucoma detection	AUC Accuracy Specificity	Better specificity	Less accuracy
Shuang et al. [121]	ResNet-34 U-Net	• A modified U-Net architecture merges a pre-trained ResNet-34 framework with conventional U-Net decoding layers to produce a powerful segmentation method for identifying glaucoma	Dice-score Mean absolute error	Enables quick training of network with fewer epochs, further prevents over-fitting, and ensures a robust performance	Images with poor quality could affect the model's segmentation performance
Mark et al. [122]	ResNet-30	• Compared the effectiveness of the development of numerous deep learning algorithms on different datasets	AUC	High accuracy	The inconsistent glaucoma definitions and labelling employed in the various datasets are one of the study's shortcomings
Yidong et al. [123]	MB-NN	• Created an MB-NN model for the diagnosis of glaucoma •Both automatic hidden features learning and domain knowledge are used	Accuracy- 0.9151%, sensitivity -0.9233%, specificity—0.9090%	Higher accuracy	Expand the experimental dataset in order to develop a more complex model and boost the performance
WangMin et al. [124]	ConvNet	• Suggested that a clinically interpretable deep learning model • The technique achieves accurate automated glaucoma detection and better explains the various zones to support the diagnosis	AUC Dice-score	High accuracy	It is challenging to represent feature maps with high resolution

Table 6 (continued)

Author	Technique	Objective	Performance	Merits	Demerits/Research Gap
Marriam et al. [125]	EfficientDet-D0 EfficientNet-B0	• Provided a model that, EfficientNet-B0 and EfficientDet-D0 for extracting key points that would improve the performance of glaucoma recognition while reducing the model's execution and training times	Accuracy	Computationally robust	Intend to assess research on other eye conditions
Qaisar [126]	CNN	• Presented a CNN method for the detection of Glaucoma	Accuracy-99% Specificity-98.01% Sensitivity-84.50% Precision-84%	Accurate detection of glaucoma	Large-scale glaucoma datasets will evaluate the Glaucoma-Deep system's practical usability
Allan et al. [127]	Google Net	•A system for automatically classifying images of the fundus to detect glaucoma	Accuracy	Better accuracy	No pre-processing technique is used
Deepa et al. [128]	UNet S-Net	• This paper introduces a UNet-SNet two-stage DL architecture for glaucoma diagnosis	Accuracy	Glaucoma can be detected easily using the deep characteristics extracted from the disc area	The functionalities of prediction are insufficient
Jinho et al. [129]	NasNet	• This study's objective was to evaluate the effectiveness of a DL classifier for SD-OCT-based identification of glaucomatous change	AUC Sensitivity specificity	The system has high sensitivity and specificity for glaucomatous structural change detection	There were insufficient datasets, and the included patients had been carefully selected for normal-tension glaucoma
Andres et al. [130]	VGG16 VGG19InceptionV3 ResNet50 and Xception	• Used five distinct ImageNet-trained models for autonomous glaucoma assessment utilizing fundus pictures	AUC, specificity, and sensitivity	The less computational time required	Glaucoma assessment using fundus image is a difficult task
Mamta et al. [131]	CNN G-Net	• This study aims to properly measure the cup-to-disk radii ratio and forecast glaucoma progression • The prior magnitude of discs and cups was divided by their current magnitude and squared to get this ratio	Accuracy Dice score	Less amount of time is required for prediction	The architecture is adaptable and has a variety of uses for other medical images

Table 6 (continued)

Author	Technique	Objective	Performance	Merits	Demerits/Research Gap
H.N Veena et al. [132]	CNN	• The study's primary goal is to find the CDR value for glaucoma progression prediction • The inputs from both models are combined to determine the CDR value • The square root of the disc area to the cup area is measured to compute the value of CDR • The optic disc and cup fields of both predicted masks are shown by the white pixel count	Dice metrics IOU F1 score SSIM Accuracy MCC	Less computational time	The developed model can be used for a variety of segmentation of medical image applications
Huazhu et al. [133]	DENet	• Glaucoma Screening from Fundus Image using DENet	AUC, specificity, and sensitivity Accuracy	High sensitivity performance	The functionalities of prediction are insufficient
Soheila et al. [134]	CNN RNN LSTM	• Developed a CNN and RNN that cooperate to extract the spatial and temporal properties from a fundus video	Sensitivity Specificity F-measure	Enhanced accuracy for detection	Due to the sample size's modest size and the population's racial homogeneity, the network accuracy will be reduced

was utilized on a pre-trained CNN framework to extract features and generate the combined feature vector. The extracted features were given as input to the classifier framework for categorizing eye diseases. The introduced framework attains better accuracy (97.8%) performance than the existing approaches. In future, different machine learning based techniques can be used to predict diabetic retinopathy diseases.

Glaret Subin and Muthukannan [141] introduced an optimized CNN framework for categorizing multiple eye diseases. At first, the input images were pre-processed utilizing the maximum entropy transformation scheme. Afterwards, pre-processed images were given as input to the CNN framework for extracting features and categorizing different eye diseases. The developed framework achieves higher accuracy (98.3%) performance than existing approaches. The proposed scheme was used for the accurate detection of different eye diseases. However, the performance of the proposed scheme can be enhanced further using an advanced deep learning framework.

Neha Sengar et al. [142] developed a deep neural network model for multiple retinal diseases. Initially, multiple class fundus images were collected from a multi-class dataset, and an augmentation process was utilized to increase the images. Afterwards, a multi-layer neural network framework was used to accurately detect multiple classes of eye diseases. Here, a keystone CNN framework was used for the extraction of features from the pre-processed images. The performance of the framework was enhanced significantly by the existing approaches. Further, the performance can be improved using an advanced deep learning technique.

Geetha Pavani et al. [143] introduced a multiple class retinal lesion segmentation and diabetic retinopathy classification using a fully automated RILBP-YNet. The proposed framework was used for the segmentation of multiple lesions. A parallel encoder was used with the traditional encoder and decoder framework to extract the texture-based features and enhance the segmentation outcomes. Here, the textual feature extractions corresponded with local binary patterns (LBPs) of respective fundus images. The obtained performance can be enhanced further with improved techniques.

Xingyuan Ou et al. [144] introduced a two stream interaction based CNN scheme for categorizing various eye diseases with bilateral fundus images. A feature enhancement module was framed using an attention process to learn the interdependence between global and local information. A multi-scale module was framed to enrich the feature maps by overlaying the feature data of various resolution images extricated via dilated convolution. The performance of the proposed framework can be enhanced further with improved data augmentation approaches. The comparison of various eye disease predictions using DL is specified in Table 7.

4.9.1 Fundus Image Based Classification

In the literature, a number of DL techniques have been explored that have produced impressive results for automatically classifying FUNDUS images. While dealing with enormous amounts of datasets and being considerably more precise than expert results, the DL models show promising outcomes in classifying eye diseases. In the field of medical FUNDUS images, numerous studies have been conducted using DL approaches for automatic categorization. In order to classify various FUNDUS disorders, this inspired the creation of a review on DL algorithms.

A DL technique for identifying curable blinding retinal disorders was introduced by Kermany et al. [83]. Mendeley received training on the following datasets: DRUSEN 8617, DME 11,349, CNV 37,206, and Normal 51,140. For the OCT image classification on the Kermany dataset, Das et al. [84] presented CNN depending on multi-scale deep feature fusion. Li et al. [86] used the Mendeley dataset to offer automated identification of retinal disorders. Alqudah [87] introduced SD-OCT utilizing automated CNN for the multi-class problem.

For the Kaggle2 dataset, Ghosh et al. [88] suggested automated DR diagnosis employing CNN and data augmentation by rotation and brightness. In addition to its stages for DR detection, Raju et al. [89] applied a modified CNN augmentation approach through Zooming, flipping, rotating, translating, enhancing colours, and centering on the five class eyepieces kaggle2 dataset. Deep CNN was suggested by Wan et al. [90] for DR classification using an image-based method. 35,126 colour FUNDUS pictures from the Kaggle2 dataset (five stages or classes: 873 severe, 5292 moderate, 2443 mild, 25,810 normal, and 708 other) were gathered. Rehman et al. [91] applied the ensemble classifier approach to the ACRIMA dataset of 705 images, ORIGA dataset of 650 images, RIM-ONE dataset of 455 images, AFIO dataset of 124 images, and HMC dataset of 55 images. Peng et al. [92] developed a DeepSeeNet framework for automatically categorizing eye diseases among 59,302 fundus images. An analysis of the number of papers reviewed for fundus images is given in Table 8.

4.10 Classification Based on Different Classes

There are three classification methods available, such as multi-label, multi-class, and binary class. The database contains three dataset types such as multi-class data (two or more classes with softmax but only one disease classified at a time), binary class data (two classes 1 or 0 with binary

Table 7 Comparison of various eye disease predictions using DL

Author and Reference	Eye disease	Architecture	Classes	Dataset	Result	Remark
Abramoff et al. [57]	DR	AlexNet	Moderate, severe NPDR, PDR(Multi class)	Messidor-2	SP–87.0%, SE–96.8%, AUC–98.0%	These algorithms may increase the effectiveness of DR screening, hence reducing the risk of blindness and visual impairment due to this deadly disease. But the aim of the study was not to assess the performance of the tool or additional DR detection techniques
Choi et al. [58]	DR	VGG-19	Normal Abnormal (Binary class)	STARE dataset	SP–85.5%, SE–80.3%, AUC–90.3%	These pilot study's prediction models were unable to demonstrate the benefit of utilizing multi-class retinal imaging datasets with deep learning of modest dataset sizes in terms of categorization accuracy
Ting et al. [59]	DR	VGGNet	Moderate NDPR Worse (Multi-class)	SIDRP	SP–91.6%, SE–90.5%, AUC–93.6%	More research is required to assess the deep learning system's relevance in healthcare settings and its usefulness in enhancing visual results
Gondal et al. [60]	DR	Supervised CNN	NRDR RDR(Binary)	Kaggle Dataset DiaretDB1 Dataset	SP–97.6%, SE–93.6%, AUC–95.4%	The inspiration for this structure came from a new, top-performing supervised CNN for DR grouping, updated to accommodate weakly supervised object localization under supervision
Gulshan et al. [61]	DR	Inception-V3	RDR No RDR(Binary)	Kaggle dataset	SE–90.1%, SP–98.2%	Additional investigation is required to establish the practical application of this technique in a clinical environment and to assess whether applying the algorithm would result in better treatment and results than the present ophthalmologic analysis

Table 7 (continued)

Author and Reference	Eye disease	Architecture	Classes	Dataset	Result	Remark
Gao et al. [62]	DR	DcardNet	Mild NPDR, No DR, Moderate NPDR, PDR(multi-label), Severe NPDR	DcardNet-36 and ResNet-18 dataset	Accuracy of 3 classes- 95.7%, 85.0%, and 71.0%	Unfortunately, OCTA networks have relatively little data compared to other medical image datasets. Training on 3D data volumes might become feasible when more OCTA data are gathered
Daanouni et al. [63]	DR	MobileNet	Drusen, DME, CNV normal(Multi label)	OCT dataset	Accuracy- 80%, precision -85%, recall -80.5%	In order to obtain high accuracy in prediction DR, this work is expanded to concentrate more on improving the accuracy of the MobileNet model and reducing complexity and latency by integrating the model with a pre-trained feature map and shallow neural network
Li et al. [64]	DR	U-Net	Binary class	e-optha EX, DIARETDB1 v2, HEI-MED, Messidor	AUC–96%	The approach is simple and applicable to identifying different forms of DR, such as microaneurysms and haemorrhages
Perdomo et al. [65]	DR	LeNet	Healthy and exudate patches	e-ophtha	Accuracy-99.8%	This study's initial findings on exudate detection were promising. The upcoming study will focus on its application to the identification of microaneurysms as well as other indications and symptoms of DR
Takahashi et al. [66]	DR	GoogleNet	NDR PDR(Binary classification)	-	ACC–81%, P ABAK -74%	An area of the retina that is normally invisible on fundoscopy is used by the DL disease staging system to assess the DR, and another DL directly recommends therapies and makes a prediction

Table 7 (continued)

Author and Reference	Eye disease	Architecture	Classes	Dataset	Result	Remark
Phan et al.[67]	Glaucoma	VGG19, ResNet152, DenseNet201	Normal, Glaucoma, Non-glaucoma(multi-class classification)	RIGA	AUC–90%	Quality images must be collected and pre-processed properly to improve the ability to discriminate
Muhammad et al. [68]	Glaucoma	CNN + RF	Healthy, Glaucomatous(Binary classification)	ORIGA	Accuracy-93.1%	In separating healthy suspicious eyes from eyes with mild glaucoma, the HDLM methodology performs better than conventional OCT and VF clinical measures. This method could be improved further, and it could be beneficial for screening
Mark et al. [69]	Glaucoma	ResNet50 and Image Net	Normal, Mild, Moderate(Multi-class classification)	ADAGES and DIGS	AUC–0.82	From an SD OCT image, DL models were highly accurate at detecting eyes with GFVD and estimating the degree of functional loss. One problem is that the results presented haven't been generalized to other populations
Sudhan et al. [70]	Glaucoma	U-Net DCNN DesNet-201	Glaucoma, Non-glaucoma(Binary classification)	ORIGA	Accuracy-98.82%	The diagnosis of breast cancer, brain tumours, and diabetic retinopathy, among other medical image segmentation and classification processes, can benefit from this model
Samuel et al. [71]	Glaucoma	-	Normal, Suspect, Glaucoma (Binary classification)	DRISTI	MAE	Early on, VAE outperformed PW in prediction, with significantly lower mean absolute errors for the fourth, sixth, and eighth visits from the first three

Table 7 (continued)

Author and Reference	Eye disease	Architecture	Classes	Dataset	Result	Remark
Shotaro et al. [72]	Glaucoma	CNN + HFA	Glaucomatous eye, non glaucomatous eye (Binary classification)	–	MAE TD value	Downsize the OCT pictures to 224 × 224 pixels in accordance with the results of the previous study43; nevertheless, this data processing resulted in information loss, which may have decreased the prediction accuracy
Juan et al. [73]	Glaucoma	VGG-19	Glaucoma(Binary classification)	–	AUC–0.94	The results of the experiments utilizing three distinct data sets and 2313 images show that this approach can be a useful alternative for building a computer assisted system for diagnosing glaucoma
Sahlsten et al. [74]	DME	Inception-V3	Binary classification	Retinal image	SP–97.4%, SE–89.6%, AUC–98.7%	The use of the DL system in clinical examinations requiring finer grading could boost the cost-effectiveness of screening and diagnosis while attaining higher than suggested performance
Al-Bander et al. [75]	DME	Softmax	Non-CSME and CSME(Binary classification)	MESSIDOR	SP–96.5%, SE–74.7%, ACC -88.8%	Additionally, researchers want to provide a better answer to the problem of data imbalance than the current oversampling approach
Prentavsic et al. [76]	DME	Softmax	Binary classification	DRiDB	SE–78%, F Sc–78%	The creation of automated screening programmes for primary recognition of diabetic retinopathy requires a completely automated output because manually segmenting and counting exudate areas is a laborious task

Table 7 (continued)

Author and Reference	Eye disease	Architecture	Classes	Dataset	Result	Remark
Tan et al. [77]	DME	Softmax	Multi-class	CLEOPATRA	SE–87.58%, SP–98.73%	According to this study, training a single CNN to accurately predict sections such as diseased features on various fundus images is feasible
Kaymak et al. [78]	DME	AlexNet	Multi-class classification	Kermany	Training accuracy: 96.6%; Testing accuracy: 93.4%	The classification of AMD as well as DME detected OCT images is demonstrated by the results to be superior to the DL based method employed in recent literature
T. Pratap et al. [79]	Cataract	AlexNet	Multiclass classification	HRF, STARE, DIARETDB0, MESSIDOR, FIRE,	ACC–92.91%	The IoT and autonomous disease detection techniques will help to significantly improve medical facilities, especially in rural regions, in modern medical diagnosis
Sarki et al. [80]	Cataract	VGG-16	Multiclass	Messidor, Messidor2, DRISHTI-GS	Accuracy of 88.3% for multi-class classification and 85.95% for the mild multi-class category	An optimum intermediate scenario of accuracy obtained is chosen to enable effective and efficient completely automated DL based system development and enhance the results of bulk screening services among the at-risk population
Ram et al. [81]	Cataract	CNN	Multi-label	ODIR-2019	An average accuracy of 0.858 and 0.883	In order to distinguish between classes like AMD and Normal, the most effective CNN, NN-2, and additional image processing approaches can be used
Wang et al. [82]	Cataract	EfficientNetB3, InceptionResNetV2	Multi-label	ODIR-2019	Accuracy: 0.92	Understanding different facets of deep neural networks and visualization is also a significant study area to increase the clinical adoption of DL models

Table 8 Analysis of the number of papers reviewed for fundus images

Reference number	Eye Disease	Fundus Photography	Classifier type	Limitations
[57]	DR	✓	AlexNet	The objective of the study was not to assess the performance of DR detection techniques
[58]		✓	VGG-19	The prediction frameworks could not demonstrate the benefit of multi-class retinal imaging datasets
[59]		✓	VGGNet	Further research was in need to evaluate the deep learning system's relevance in healthcare settings and its benefits in improving visual outcomes
[60]		✓	Supervised CNN	More research is required to assess the deep learning system's relevance in healthcare settings and its usefulness in enhancing visual results
[61]		✓	Inception-V3	Further investigation is needed to provide practical application and to assess whether the algorithm would result in better results than the present analysis
[64]		✓	U-Net	The performance needs to be improved with multiple class predictions
[65]		✓	LeNet	Future studies need to focus on their application to identify microaneurysms and other indications and symptoms of DR
[66]		✓	GoogLeNet	A retinal region is typically invisible on fundoscopy; other modalities can be used for disease prediction
[67]	Glaucoma	✓	ResNet50 and Image Net	Quality images should be gathered and processed to enhance the discrimination ability
[69]		✓	Hybrid DL	The major issue is that the results presented haven't been generalized to other populations
[70]		✓	U-Net	A large amount of datasets can be incorporated to validate the performance
[71]		✓	VAE	VAE performance can be enhanced further for better classification of diseases
[73]		✓	CNN	The results of experiments utilizing three distinct data sets proved that this approach can be a useful alternative for building a computer assisted system for diagnosing glaucoma. Still, an advanced scheme needed disease prediction
[135]		✓	MLP based ANN	A further improved approach was required for predicting different types of eye diseases
[74]	DME	✓	Inception-V3	The DL system needs finer grading to boost the cost-effectiveness of diagnosis while achieving higher than suggested performance
[75]		✓	Deep neural networks	The researchers need to resolve the data imbalance issue better than the current oversampling approach
[76]		✓	CNN	Automated outcome is needed to enhance performance
[77]		✓	CNN	Feasible outcomes can be achieved by using further advanced approaches
[45]	hypertension	✓	Retinal nerve fibre layer	The comparative analysis was not effective for the validation
[69]		✓	Hybrid DL method	The major issue is that the obtained results haven't been generalized to other populations
[85]		✓	Transfer learning	The execution time of the process is very high

Table 8 (continued)

Reference number	Eye Disease	Fundus Photography	Classifier type	Limitations
[79]	Cataract	✓	AlexNet	The obtained performance is limited and needs further improvements
[80]		✓	VGG-16	An automated DL based system was in need to enhance the results of bulk screening services
[81]		✓	CNN	Additional advanced approaches are needed to differentiate classes like AMD and Normal
[82]		✓	Efficientnet	Various stages of deep neural networks and their visualization needs a study area to increase the clinical adoption of DL models
[88]		✓	CNN	Accuracy performance can be improved further using complex denoising approaches
[89]		✓	CNN	Further research advancement needs to be confirmed on the automatic classification of eye diseases
[90]		✓	DCNN	The obtained outcomes are limited
[91]		✓	DCNN	Need further enhancements in outcomes
[92]		✓	DeepSeeNet	The training time of the process is much higher
[81]	Myopia	✓	CNN	Additional advanced approaches are needed to differentiate classes like AMD and Normal
[82]		✓	Ensemble model of InceptionResNetV2 and EfficientNetB3	Different stages of deep neural networks and their visualization needs a study area to increase the clinical adoption of DL models
[111]	AMD	✓	DCNN	The performance outcomes are very limited
[112]		✓	SVM	Need to improve the accuracy performance
[113]		✓	Explainable DL	Achieved good accuracy performance, but the execution time must be lower
[114]		✓	Artificial intelligence technique	The further advanced scheme required performance improvement
[101]	Multi-label	✓	CNN	Need advanced scheme for better performance improvement
[102]		✓	CNN	Need to reduce the execution time of the process
[103]		✓	CNN	The obtained outcomes are very limited
[104]		✓	VGG-16 transfer learning	Performance analysis should be performed with different metrics
[93]	Multi-class	✓	CNN	The attained results are still limited
[94]		✓	GoogleNet and DL	Achieved good performance with higher processing time
[95]		✓	Deep DR-Net	Attained better accuracy with other limited performances
[96]		✓	Ensemble approach	Data imbalance is the major issue of the work
[97]		✓	Transfer learning	Need to increase the size of the data for more validations
[98]		✓	DCNN	More performance measures can be performed
[99]		✓	ResNet and GoogleNet	Data sources can be increased for more validations
[100]		✓	CNN	Need an advanced form of approach for better performance validation

cross entropy), and multi-label data (more than one disease occurring instantaneously in a single image). The number of papers reviewed in various classes is depicted in Fig. 8.

4.10.1 Multi-Class Classification for Eye Disease Prediction

On the Kaggle dataset (80,000 photos), Pratt et al. [93] suggested a proprietary data augmentation and CNN procedure for DR diagnosis and achieved an accuracy of 75%. A CNN model for identifying image tessellation on 12,000 samples was described by Lyu et al. in [94]. Using GoogleNet and the DL technique, the best accuracy and AUC were 97.73% and 0.9659, respectively. The FINDeRS dataset of 315 retinal images includes five classes (18 Severe DR, 32 Moderate DR, 52 Mild DR, 38 PDR and 175 Non- DR). Ardiyanto et al. [95] used the Deep DR-Net method and achieved accuracy for two classes of 95.71% and three classes of 60.28%.

Orlando et al. [96] offered a unique way of identifying red lesions using the ensemble method on the Messidor dataset (1200 pictures), and they were successful in achieving an AUC of 0.911 and 0.972. According to Bali et al. [97], the creation of the multiclass multilabel eye disease classification system was based on a significant number of fundus images, which were randomly cropped on width and height, yielding accuracy of 91%. When Raghavendra et al.

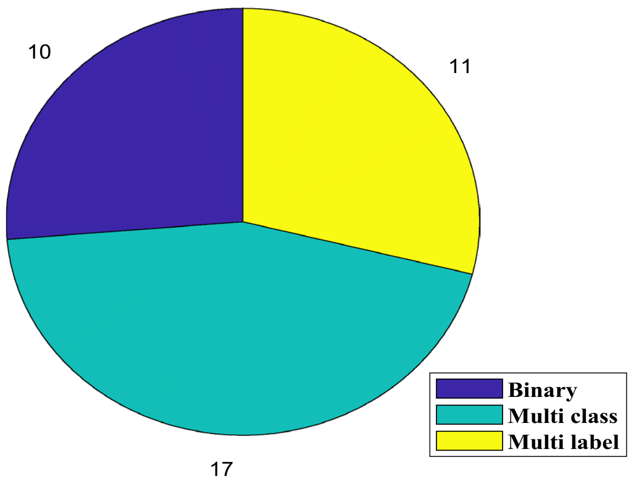

Fig. 8 Number of papers reviewed in various classes

[98] used a bespoke image dataset of 1426 photos acquired from Kasturba College, Manipal, for glaucoma detection, they were able to attain an accuracy of 98.13.

Serener et al. [99] developed an early as well as innovative glaucoma diagnosis approach employing augmentation, googlenet and resnet50 using a modified image dataset of 1544 fundus images and a RIM-ONE dataset of 158 images. They achieved a resnet and googlenet accuracy of 0.86 and 0.85, respectively. In order to better categorize retinal fundus images, S. Gayathri et al. [100] introduced a new CNN model (Binary and Multi-class Classification). For Kaggle and Messidor data, the K-score was 99.9, the f1-score was 0.99, and the accuracy was 99.75%.

4.10.2 Multi-Label Classification for Eye Disease Prediction

M. S. Alabshihy et al. [101] used explicit methods, including issue transformation, segmentation, multi-label CAD system, and MSVM on a database called DiaretDB with two classes identified as DR and hypertension. In this work, overall accuracy was obtained as 96.1%. A categorization model for eight ocular disorders was developed by T. Islam et al. [102], employing differences in restricted adaptive histogram equalization as a pre-processing step. CNN was employed for feature extraction and reached a 31% kappa coefficient, 85% f1-score, and an AUC of 80.5%. Similarly, a review analysis over multiple eye image classification was carried out by Kumar, Y. and Gupta, S in [137], which analyzes the deep transfer learning model for efficient multi-class classification. The analyzed models have achieved a 98.9% accuracy (ResNet 50) and 98.4% accuracy (Xception model). The categorization of diabetic retinopathy using deep learning techniques for multiple class imbalanced databases. Manisha Saini and Seba Susan [103] introduced a deep learning network for the multiple categorization of eye diseases. The obtained classes were mild, moderate, severe and proliferate classes of diseases. Utilizing VGG-16 transfer learning on two techniques, N. Gour et al. [104] presented a classification of ophthalmic diseases in this study.

The analysis of deep learning techniques for predicting eye diseases has provided valuable insights into the potential of these methods. Several studies have explored the use of deep learning models, such as CNNs, for detecting and classifying various eye diseases. One key finding from the related works is that deep learning models have demonstrated high accuracy and performance in the detection of common eye diseases, including diabetic retinopathy, glaucoma, and age-related macular degeneration. These models have shown promising results in sensitivity and specificity, outperforming traditional machine learning algorithms and even human experts in some cases. Moreover, deep learning models have shown potential in the early detection of eye diseases, which is crucial for timely intervention and effective treatment.

Furthermore, the analysis of the related works has highlighted the importance of high-quality and well-annotated datasets for training deep learning models in the context of eye disease prediction. The availability of large-scale datasets with diverse patient populations and comprehensive clinical information is essential for training robust and generalizable models. The deep learning techniques for the prediction of eye diseases have demonstrated their potential for accurate and early detection of various eye conditions. However, further research is needed to address the aforementioned challenges and ensure the practical implementation of these techniques. With continued advancements in technology and collaboration between researchers, deep learning models can potentially enhance eye disease predictions.

4.11 Challenges and Limitations

While deep learning techniques hold great potential in predicting eye diseases, they also face several challenges and limitations. Some of the key challenges include:

- Deep learning models require large and diverse datasets to learn representative features and generalize to unseen data. However, acquiring annotated medical imaging datasets with sufficient cases for rare eye diseases can be challenging. Additionally, datasets may suffer from class imbalance, where certain eye diseases are underrepresented, leading to biased predictions and reduced performance for minority classes.
- Deep learning models typically require a large amount of labelled data for training. Obtaining a diverse and well-annotated dataset for eye diseases can be challenging,

especially for rare conditions. Limited dataset size can lead to over fitting and reduced generalization ability of the model.

- In eye disease classification, certain conditions may be less prevalent than others, resulting in a class imbalance in the dataset. This can lead to biased models prioritizing the majority classes while struggling to accurately classify the minority classes.
- Annotated data for eye diseases is typically obtained through manual expert labelling, which can be time-consuming and costly. Additionally, due to privacy concerns, medical data may not always be readily available for research. These factors limit the accessibility and quantity of labelled data, hindering the training and evaluation of deep learning models.

5 Conclusion

In conclusion, the analysis of deep learning techniques for the prediction of eye diseases, as presented in this systematic review, highlights the potential of these techniques in revolutionizing the field of ophthalmology. Through a comprehensive examination of various studies, this review has demonstrated that deep learning models have shown remarkable performance in accurately diagnosing and predicting eye diseases. One of the key findings of this review is that deep learning algorithms can effectively analyze large amounts of medical imaging data, such as retinal images and OCT scans, to identify subtle patterns and features that are difficult for human experts to detect. This ability can significantly enhance the early detection and diagnosis of eye diseases, leading to timely interventions and improved patient outcomes.

Moreover, the systematic review has revealed that deep learning models have achieved impressive accuracy in detecting specific eye conditions, including diabetic retinopathy, age-related macular degeneration, DME, cataract and glaucoma. These findings suggest that deep learning techniques hold promise for developing automated screening systems that can aid healthcare professionals in identifying and monitoring eye diseases more efficiently and effectively. However, it is important to acknowledge that there are still certain challenges and limitations associated with implementing deep learning techniques. Issues such as data availability, interpretability of the models, and generalizability across diverse patient populations need to be addressed to ensure these algorithms' reliability and ethical use. Overall, this systematic review highlights the significant progress in applying deep learning techniques to predict eye diseases. The findings suggest that deep learning models have the potential to play a role in eye disease prediction, enabling earlier detection and more accurate diagnoses.

6 Future Scope

This part raises a number of research questions that scientists have been unable to address in prior ED detection studies. Therefore, additional study is still required to increase the efficiency of various ED detection methods. The following list outlines the research issues that need to be resolved.

- It is challenging to develop further and produces another efficient DNN despite DL has demonstrated incredibly favourable achievements in medical imaging. A different strategy might be to develop a renal disease diagnostics and object-based model instead of an image-based one.
- For learning purposes, a lot of retinal fundus images are used frequently. If the training dataset is less, accurate findings cannot be achieved. Potential solutions with various enhancing techniques such as colour setting, cropping, shifting, and rotating should be used first rotation, cropping, translation, and setting colour.
- Many object recognition DL frameworks are accessible for retraining on a new set of images like medical images, including AlexNet, VGGNet, LeNet and GoogLeNet. However, these structures are less effective at classifying medical images, which makes them less suited for this application.
- Particularly rural areas struggle with the decrease in human resources, especially in the healthcare sector. Telehealth can therefore be quite helpful in these situations in overcoming this disadvantage. To diagnose ED from telemedicine, neural networks, cloud computing, and eye fundus images may be merged in the future.

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