REVIEW ARTICLE

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Deep Learning Approaches for Retinal Disease Identification in Fundus Imaging: A Comprehensive Overview

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ABSTRACT

Vision impairment is becoming a major health concern, especially in elderly people. While in the medical field, manually detecting ocular pathology has significant difficulty. Therefore, deep learning diagnostic techniques are widely used for identifying eye diseases and play a crucial role in diagnosing vision-related problems. Examination of fundoscopy allows for analyzing eyes for diagnosis of eye diseases, including Diabetic retinopathy (DR), Cataracts, Glaucoma, Age-related macular degeneration, Pathologic Myopia, and more. In this paper, we propose a concise review of introducing most of the DL, hybrid, and ensemble models utilized for the purpose of identification and classification of eye diseases. Various datasets, feature extraction techniques, and metrics for performance evaluation are discussed. The chosen papers come from conferences and scholarly publications published from 2019 to 2024. We evaluate the performance of chosen researches using different datasets, the most common ones include ocular disease intelligent recognition, Indian DR image dataset, EyePACS, methods to evaluate segmentation and indexing techniques in the field of retinal ophthalmology, methods to evaluate segmentation and indexing techniques in the field of retinal ophthalmology-version 2, DIARETDB, Structured analysis of the retina, high-resolution fundus, digital retinal images for vessel extraction, online retinal fundus image dataset for GI analysis and research, retinal fundus multi-disease image dataset and Kaggle datasets. The detection studies that have been reviewed show that the accuracy of these approaches varies between 73% and 99%, the sensitivity ranges from 69% to 99% and precision is between 89% and 99%. The results show that great accuracy is consistently achieved with DL algorithms compared to traditional Machine learning approaches. However, there are still some challenges and limitations remaining including excessive resource consumption and over-fitting due to dataset size and diversity issues. This review offers useful insight for researchers and healthcare professionals to comprehend AI technologies properly for the detection, classification, and diagnosis of retinal diseases. We succinctly summarize the methodologies of all the chosen studies and focus on the elements that define the aim of the studies.

Index Terms: Eye Diseases, Retinal Disease Diagnosis, Color Fundus Mages, Hybrid Deep Learning, Deep Learning

1. INTRODUCTION

The eyes are considered to be one of the most important sense organs for daily functioning and crucial for observing and perceiving the outside world. Eyesight problems are experienced by almost everyone at some point in their lives. Over the years, ophthalmologists and healthcare centers always trying to find treatments and cures for people with retinal disorders that cause blindness. The World Health Organization reported in August 2023 that at least 2.2 billion individuals suffer from a sightedness problem. They state that all ages can be affected by vision loss, but most individuals who experience vision impairment and blindness are over 50 [1]. In 8 out of 10 cases, blindness can be prevented or

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avoided with early intervention or suitable treatment, but before providing an appropriate treatment for a patient's health problem getting the right identification and disease diagnosis is a key aspect of healthcare problems.

A particular type of machine learning known as "deep learning" (DL), which involves training multi-layered artificial neural networks to find patterns in data. The development and improvement of highly effective DL techniques have grown in healthcare as a promising tool for disease detection and classification, Drug identification and recognition, Medical image analysis and diagnosis, image segmentation, and recognize particular anatomical features or lesions. Thus, to improve the quality of treatment and health for patients, physicians, and other medical professionals, DL is being implemented in the present healthcare system [2].

Obtaining a retinal image using the appropriate medical image modality is the initial stage in the process of detecting and diagnosing retinal disorders [3]. With the invention of various imaging modalities over the years, "Retinal or fundus photography" has become more well-known because it is a fast and straightforward procedure while also considerably cost-effective and non-invasive. It is capable of capturing the retina, blood vessels, optic disc (OD)/cup (OC), macula, fovea, and posterior pole on the interior surface of the eye [4], see Fig. 1. Fundus photography images can hold and indicate some serious abnormities in diseased eyes including Diabetic retinopathy (DR), glaucoma (Gl), cataract (CA), Age-related macular degeneration (AMD), hypertension, Pathologic Myopia, and other diseases, which are the primary worldwide causes of blindness and visual impairment. Fig. 2. shows fundus images of various retinal disorders.

Diabetes patients may experience visual loss and blindness due to a condition called DR. Certain lesions in the eyes are caused by DR, and over time, these lesions can lead to

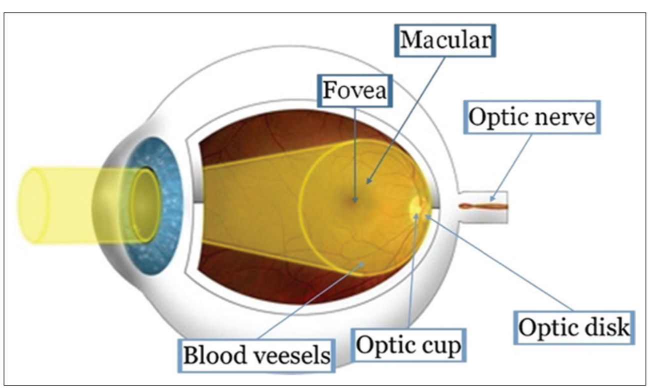

Fig. 1. Color fundus photography [5].

permanent blindness. Lesions include microaneurysms (MAs), hemorrhages (HAs), exudates (EXs), cotton wool spots, and abnormalities in retinal blood vessels [6]. The International Agency for the Prevention of Blindness reports one in three diabetic people have some kind of DR, and one in ten will experience a vision-threatening condition. DR has 4 stages, Mild, Moderate, Severe non-proliferative retinopathy (NPDR), and Proliferative DR (PDR). MAs, or tiny bulges in the blood vessels of the retina, can leak fluid into the retina in the early stages of the disease (Mild). In addition, this may result in macula swelling, which impairs vision. At this point, symptoms are typically minimal or non-existent. During the Moderate phase, the retina's blood vessels enlarge and may block. This may exacerbate diabetic macular edema (DME), a condition in which fluid accumulates in the macula area of the retina and impairs or destroys vision. The number of blocked blood vessels in the eye is growing in Severe NPDR. Retinal growth of new blood vessels is subsequently signaled. One may experience fuzzy vision with dark spots if the blood vessels totally close off. The retina loses oxygen in the last stage (PDR), and new blood vessels develop inside the retina and into the vitreous gel, which fills the eye. These blood vessels are fragile and could burst and hemorrhage [7].

Another common eye disease is Gl, which is caused by damage to the optic nerve that connects the eye to the brain. Usually, it results from fluid accumulation in the anterior chamber of the eye, which raises intraocular pressure. Although it can afflict individuals of any age, folks in their 70s and 80s tend to be the most affected [8].

A CA is a disorder in which the normal lens of the eye gets clouded. When the proteins in your lens degrade, objects appear foggy, fuzzy, or less vibrant. If someone has this eye condition, their vision may shift to the point where they see bright colors as faded or yellow instead, they may see double or ghostly images out of their eyes. Experiencing increased light sensitivity, and/or having poor night vision. It is necessary to inform your ophthalmologist if you experience any of these signs of a CA [9].

Another typical condition affecting the eye's focus is known as nearsightedness or myopia when far objects appear blurry while close-up items appear clear. For example, you can see clearly enough to read a map, but not well enough to drive a car. For several decades, the prevalence of myopia has been rising and nearly half of the world's population is predicted to be nearsighted by 2050. Other indications of myopia include headaches, eyestrain, and squinting to see clearly [10].

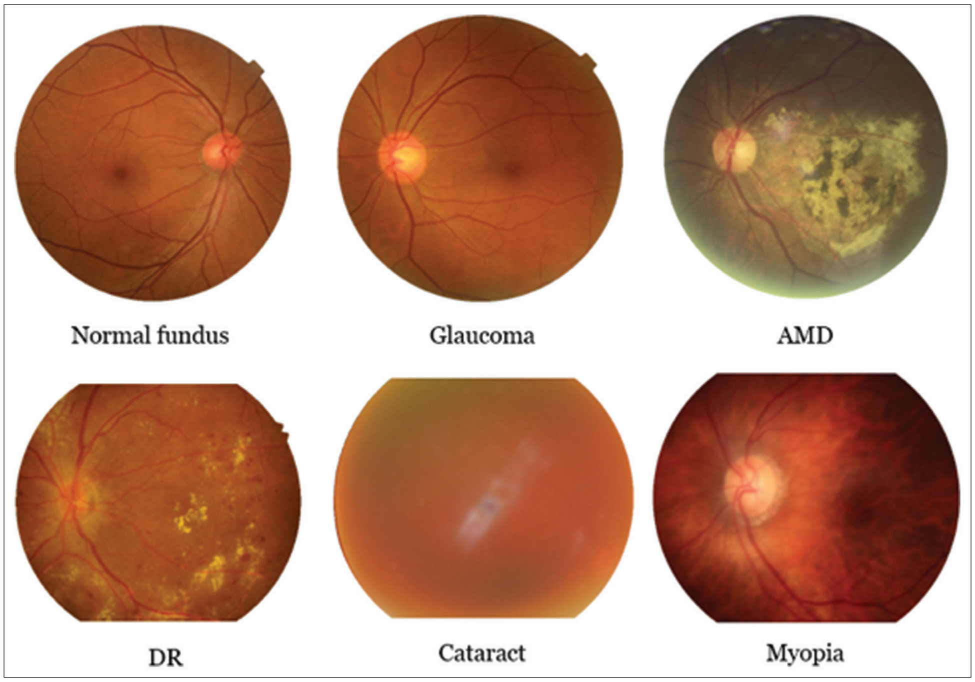

Fig. 2. Fundus images with different eye conditions.

AMD is a retinal issue. AMD is quite prevalent and it is one of the main causes of visual loss in those over 50. It occurs when there is damage to the macula (a portion of the retina). Loss of center vision is a symptom of AMD. However, your side vision, or peripheral vision, will remain normal. Whether you are looking at something close up or far away, you cannot see fine details. Consider the scenario where you are staring at a clock that has hands. While you have AMD you may be able to see the numbers around the edge of the clock clearly, but not the hands [11].

This paper aims to offer a systematic review to shed light on the advancements made in DL, hybrid, and ensemble-based techniques that are especially intended to recognize, classify, and grade retinal conditions. By focusing on recent research publications, we critically evaluate existing methodologies, highlight their advantages and limitations, and identify emerging trends. The ultimate goal is to provide insights that guide future research toward developing more accurate, explainable, and clinically viable AI-based diagnostic tools.

2. METHODS

2.1. Retinal Image Databases

In this section, we provide information about the datasets used for retinal disease diagnosis. The datasets used by the studies comprise private and publicly accessible ones. Table 1 shows the summary of fundus image datasets for diagnosing retinal disorders

2.1.1. Indian DR image dataset (IDRiD) [12]

It is a publicly available retinal fundus image database that provides information on disease severity grading of DR and DME. Furthermore, provides different retinal lesions associated with DR. Including MAs, Hemorrhages (HEs), and Soft & Hard EXs. It consists of a total of 516 images, which contain images marked with DR and/or DME and 134 Normal ones (without signs of DR and/or DME).

2.1.2. High-resolution fundus (HRF) image database [13]

The dataset is public and freely available for research purposes. Presently, there are 15 images in the database showing healthy ones, 15 of them showing patients with DR, and the other 15 images showing patients with Gl. For every image, binary gold standard vessel segmentation images are supplied Budai and Odstrcilik [14].

2.1.3. Methods to evaluate segmentation and indexing techniques in the field of retinal ophthalmology (Messidor) [15]

The purpose of the Messidor database is to support research on computer-aided diagnosis of DR. The French Ministry of Research and Defense supported the Messidor

Table 1: Summary of fundus image datasets for diagnosing retinal disorders

Dataset	Samples	Image distribution pre-class	Purpose	Disease diagnosis	Studies
DRIVE [17]	40	N: 33|Mild DR: 7	Blood vessel segmentation	DR	[38]
IDRiD [12]	516	N: 134|Mild DR: 20, Moderate DR: 136|severe DR: 74|PDR: 49	Detection, Segmentation, and grading	DR and DME	[38]–[42]
RFMiD [19]	3200	N: 669|DR: 632|ARMD: 169|MYA: 167|Other 43 categories: rest	Multi-disease Classification	46 conditions	[41], [43], [44]
ODIR [21], [22]	6426	N: 3098|DR: 1406|GL: 224|CA: 265|AMD: 293|H: 107|MYA: 242|other diseases: 791	Multi-Label multi-class Classification	8 conditions	[39], [41], [45] –[50]
Messidor [15]	1200	-	Exudates Detection, DR Grading, and OD/OC segmentation	DR and DME	[37], [39], [40], [50]–[52]
Messidor-2 [15], [23]	1748	RDR: 455|NRDR: 1286	DR diagnosis and lesion segmentation	DR and DME	[39], [42], [51], [53]
STARE [54]	20	N: 10|non-N: 10	Blood vessel segmentation	-	[38], [40], [55]
HRF [13]	45	N: 15|DR: 15|GL: 15	DR diagnosis and Blood vessel segmentation	DR and Glaucoma	[38], [41]
ORIGA [24]	650	N: 482|GL: 168	Glaucoma diagnosis and OD/ OC segmentation	Glaucoma	[40], [56], [57]
REFUGE [25]	1200	N: 1080|GL: 120	Glaucoma classification and OD/OC segmentation	Glaucoma	[57]
DIARETDB0 [27]	130	N: 20|DR: 110	MAs, HMs, H&SO EXs segmentation	DR	[50]
DIARETDB1 [29]	89	N: 5|Mild NPDR: 84	DR grading	DR	[42], [50]
ARIA [17]	450	-	ONH boundary Segmentation	AMD and DR	[40]
DRISHTI-GS [30]	101	-	ONH segmentation	Glaucoma	[39], [51], [58]
DRISHTI-GS1 [32]	101	N: 31|GL: 70	ONH segmentation	Glaucoma	[56]
Kaggle (EyePACS) [33]	88,702	-	DR grading	DR	[37], [59], [60]
Kaggle (APTOS-2019) [34]	3662	-	DR grading	DR	[61]–[63]
Kaggle (eye disease classification) [35]	4217	N: 1074|CA: 1038|DR: 1098|GL: 1007	Multi-class Classification	DR, GL, and CA	[36], [64]

DRIVE: Digital retinal images for vessel extraction, IDRiD: Indian DR image dataset, HRF: High-resolution fundus, STARE: Structured analysis of the retina, RFMiD: Retinal fundus multi-disease image dataset, ODIR: Ocular disease intelligent recognition, ORIGA: Online retinal fundus image dataset for Gl analysis and research, REFUGE: Retinal fundus Gl challenge, DIARETDB0: Standard DR database calibration level 0, DIARETDB1: Standard DR database calibration level 1, ARIA: Automatic retinal image analysis, APTOS-2019: Asia Pacific Tele-Ophthalmology Society 2019, DR: Diabetic retinopathy, ONH: Optic nerve head, AMD: Age-related macular degeneration, EXs: exudates, MAs: microaneurysms, PDR: Proliferative DR, NPDR: retinopathy (NPDR)

research program as part of the 2004 TECHNO-VISION program. This database includes 1200 TIFF images with an Excel file containing each image's medical diagnosis. ADCIS [16].

2.1.4. Digital retinal images for vessel extraction (DRIVE) [17]

DRIVE dataset has been created to facilitate comparative research on blood vessel segmentation in retinal pictures. The images used in the DRIVE database were from a Dutch study that screened for DR. There are two sets of 40 photographs total: a training set and a test set, each with 20 images. 7 exhibit mild early DR and 33 do not exhibit any indications of the condition.

2.1.5. Structured analysis of the retina (STARE) [18]

Stare is a dataset where its challenge is in the retinal vessel segmentation and this is used in medical analysis. Out of the total twenty fundus color retinal images in the STARE dataset, ten are healthy ocular fundus images and the other ten ocular fundus images are unhealthy. The dataset contains two sets of hand-annotated images segmented by two human experts as ground truth for retinal blood vessel segmentation methods. STARE: A Retinal Image Dataset [18].

2.1.6. Retinal fundus multi-disease image dataset (RFMiD) [19]

A retinal image collection called RFMiD is made available to the public. It includes 3200 photos annotated by experts that were taken with three distinct fundus cameras. Three subsets of the dataset are created: 20% for evaluation (640 photos), 20% for testing (640 images), and 60% for training (1920 images). Dataport [20]

2.1.7. Ocular disease intelligent recognition (ODIR) [21], [22]

ODIR-5K is a structured ophthalmic database of 5,000 volunteer patients along with age, color fundus images (CFI) of their left and right eyes, and diagnostic keywords performed by expert ophthalmologists. The images are saved in JPG format with various sizes and dpi values. The diseases are labeled in a CSV file with only one letter including Normal (N), CA (C), Gl (G), Diabetes (D), AMD (A), Pathological Myopia (M), Hypertension (H) and Other diseases/abnormalities (O)

2.1.8. Methods to evaluate segmentation and indexing techniques in the field of retinal ophthalmology-version 2 (Messidor-2) [15], [23]

The Messidor-2 dataset is a set of 874 DR examinations (1748 images), with two macula-centered eye fundus images one per eye. It is free to use for academic and research purposes and is not affiliated with any commercial interest. The dataset also comes with a spreadsheet showing the pairing of images. Annotations like a "ground truth' for DR are missing in them. Messidor-2 can be used, free of charge, for research and educational purposes at Messidor2: A Retinopathy Dataset [23].

2.1.9. Online retinal fundus image dataset for Gl analysis and research (ORIGA) [24]

This dataset incorporates 650 retinal photographs annotated by qualified experts from the Singapore Eye Research Institute. It was created to diagnose Gl and to segment the OD and OC. For every image presented the CDR value, the OD and OC boundaries, and a label identifying the presence or absence of Gl. The public can access ORIGA upon request.

2.1.10. Retinal fundus Gl challenge (REFUGE) [25].

An openly available data set of 1200 fundus photographs with clinical Gl labels and ground truth segmentations is provided by REFUGE. Online available at Orlando *et al.* [26].

2.1.11. Standard DR database calibration level 0 (DIARETDB0) [27]

This database includes 130 retinal images that were captured with a 50° field of view digital fundus camera. About 20 of the 130 photos are in good health, and the other 120 show signs of DR. Each image is labeled with the presence or absence of red tiny dots, hemorrhages, hard EXs, soft EXs, and neovascularization. Available through the webpage at DIARETDB0 [28].

2.1.12. Standard DR database calibration level 1 (DIARETDB1) [29]

Retinal fundus images in this database are 89. 84 of them show mild NPDR, and the remaining 5 photos are normal. The photographs were taken with a camera with a 50° field of view. Both the DIARETDB1 and DIARETDB0 databases provide images with a resolution of 1500 × 1152.

2.1.13. Automatic retinal image analysis (ARIA) [17]

There are 450 images in the JPEG format ARIA database and they were annotated by two expert ophthalmologists. Three groups are created from those images: one with AMD, one with DR, and one with a healthy control group.

2.1.14. DRISHTI-GS: Retinal image dataset for optic nerve head segmentation [30]

A dataset of retinal images for OD and OC segmentation. A total of 101 photos make up the DRISHTI-GS collection. 50 training and 51 testing photos make up the set. With the patients' permission, every photograph was taken at the Aravind Eye Hospital in Madurai. The dataset is available at Drishti-GS: Glaucoma Dataset [31].

2.1.15. DRISHTI-GS1: Retinal image dataset for optic nerve head segmentation [32]

This dataset is an extension of DRISHTI-GS. It contains 50 and 51 training and testing images, respectively. Manual segmentations are obtained for both the OD and OC regions of each image from 4 different human specialists with differing levels of clinical experience. A dataset was recently made publicly available at Drishti-GS: Glaucoma Dataset [31].

2.1.16. Kaggle (EyePACS): Kaggle dataset for DR [33]

The dataset consists of 88,702 high-definition retinal photos obtained in diverse imaging conditions. Each image has a clinician's rating, from 0 to 4, indicating the presence of DR. This Kaggle dataset consists of 35,126 training samples and 53,576 test samples in total. It is available on Kaggle [33].

2.1.17. Kaggle: The Asia Pacific Tele-Ophthalmology Society 2019 (APTOS-2019) [34]

The Kaggle dataset has 3662 samples gathered from numerous people in rural India and then it was arranged by the Aravind Eye Hospital. The fundus images were taken over an extended period in various settings and situations. There are five categories for the samples based on DR Disease Severity. It is available on Kaggle [34].

2.1.18. Kaggle (eye_diseases_classification) [35]

The dataset includes more than 1000 retinal images per class, including those for normal, DR, CAs, and Gl. Totally, this dataset includes 4217 fundus images of three different kinds of eye diseases and a normal class as well. The sources of such images are diverse and include IDRiD, Ocular recognition, HRF, and others. It is available on Kaggle [35].

2.2. Pre-processing Stage

Images typically vary in brightness, intensity, and visual quality. In this section, we discuss pre-processing methods frequently employed for fundus image analysis. Gaining the data in a structure and shape, while also cleaning raw data to build and train Convolutional Neural Network (CNN) and machine learning models. Attaining greater accuracy is a crucial stage in this process. Pre-processing retinal pictures is typically necessary for the prediction of eye diseases to increase model performance and accuracy. Table 2 provides an overview of various pre-processing methods used in ocular disease diagnosis studies.

Pre-processing the retinal photographs to extract the Region of Interest (ROI) is the first step in Kadum *et al.* [36]. After that, they utilized suitable image-processing methods to separate the pertinent regions associated with every individual ocular condition. This reduced the impact of background noise and unnecessary image areas to concentrate the analysis on the areas with abnormalities related to the disease. After the ROI extraction, we scaled the pictures to 512 × 512 pixels, which is a common size. This process guaranteed uniformity in the input data and enabled effective feature extraction.

Developing a hybrid image enhancement algorithm to improve the quality of pictures is proposed in the study [37]. Thus increasing contrast and reducing noise to support the standard of color fundus imaging. There are two main phases to the approach: First chopping images to remove unnecessary information. Then the use of Gaussian blurring and cropping to improve contrast and reduce noise. After receiving retinal fundus photographs, the Fundus Image Enhancement (FGB) model identifies the foreground and uses Gaussian blurring to highlight the retinal vessels. Followed by feature extraction and classification.

This dataset [65] is used by Londhe [66] consisting of (300) normal and 3 other categories (100/category) of eye diseases. Images come in a variety of dimensions. The pictures were resized to the same dimensions. Then, the black background of the images is removed with cropping and resized again to 224 × 224. Then, the augmentation step is performed (horizontally and vertically flipping) to ensure that each class has 300 images. The dataset is split into 70%, 10%, and 20% for training, testing, and validation, respectively. Normalization as a data transformation step is utilized next, in which 8-bit channels of the colors red, green, and blue are used to represent images.

In hybrid [53] the dataset used is Decencière *et al.* [15], Messidor2: A Retinopathy Dataset [23], which consists of variously sized photos. Thus, their resolution changed to 960w × 1200h. After that normalization operation is performed before providing images as input to a DL model, each image's pixel values should be scaled, from the range of [0–255] to the of [0–1] by dividing them to 255. Finally, the feature extraction procedure receives pre-processed images.

The pre-processing algorithm proposed in Xu *et al.* [62]. Starting by cropping the image's non-retinal portion. Gaussian Blur method is used for enhancement of images which improves contrast and reduces noise. For comparative purposes in later experiments, a colored version of the clipped image is additionally processed. Automated and Center cropping were also carried out. Data augmentation is finally applied to the pre-processed dataset [34] to prevent over-fitting and expand the dataset's diversity.

The first step in Menaouer *et al.* [63] for pre-processing was reading images and resizing them to 128 W ×128 H. To enhance the CNN models' training performance, the pixels are normalized. Then, to reduce overfitting, real-time image augmentation was used, and to distribute the data evenly among the severity levels of DR. After augmentation, 5000 photos were obtained for each class. Finally, hybrid DL approaches used the generated images as input.

In Mahmoud *et al.* [67] a system was employed to optimize the brightness, illumination, and equalization of the photographs. The pre-processing step involves enhancing the contrast and brightness of the input photos and removing any unwanted background details. To enhance image clarity, colorful fundus photos are normalized to a specific luminance level.

For this study [57], pre-processing was carried out in two stages, (1) RGB2GRAY: authors converted RGB images to grayscale because Retinal images in grayscale mode are better than RGB at extracting and identifying textural features, additionally lowering the noise and improving the outcome.

Table 2: Pre-processing methods used in chosen studies

No.	Studies	Pre-processing methods	Strengths	Weaknesses
1	Doddi [36]	• ROI extraction • Resizing	• Focuses on relevant regions that include crucial information, standardizes the size to ensure consistency across input data	• This may result in the loss of peripheral details and useful information
2	Abbood *et al.* [37]	• Greyscale image cropping • Circle crop and GaussianBlur	• Performs foreground identification of fundus images and applies Gaussian blurring to enhance the visibility of retinal vessels	• Circular cropping may remove valuable information
3	Retina_ Dataset [66]	• Cropping • Resizing • Data augmentation (flip vertically & horizontally) • Normalization	• Eliminates redundant regions, increases dataset diversity, enhances model generalization, and accelerates the training process	• Data augmentation may introduce unrealistic transformations
4	Khan *et al.* [53]	• Resizing • Normalization	• Standardizes input images for CNNs and preferred in DNN model training	• Not applying de-noising techniques or contrast enhancement (e.g., CLAHE)
5	Butt *et al.* [62]	• Cropping • GaussianBlur pre-processing (image enhancement) • Color version of cropping & GaussianBlur's pre-processing • Auto cropping • Center cropping	• Multiple enhancement techniques improve adaptability, by automatically cropping the ROI based on the retinal image's properties; the automatic cropping algorithm can increase pre-processing's accuracy and efficiency.	• Certain techniques may distort important features and destroy the color information of the image
6	Xu *et al.* [63]	• Resizing • Normalization • Augmentation • Dataset splitting into 50:25:25 (Train, Test, and Val)	• These steps enhance processing efficiency, improve model performance, increase dataset diversity, and ensure reliable evaluation	• The model may struggle with noise and changes in image quality because the authors didn't introduce techniques to reduce noise or improve contrast in their pre-processing steps
7	Londhe [67]	• Contrast enhancement	• Images often differ in intensity, brightness, and quality, Standardizing these factors helps improve the performance of the ML algorithm	• May amplify noise
8	Thanki [57]	• RGB2GRAY • Texture feature extraction (by Gray-Level Co-Occurrence Matrix)	• Reduces computational complexity as grayscale images have Fewer Channels to Process, extracts important texture features	• Loss of color information and reduce models performance for tasks that depend on color features
9	Nawaldgi and Lalitha [59]	• Image resizing • Data augmentation • Applying a median filter • Image sharpening	• Enhances image quality, reduces noise	• Sharpening can introduce noise or unwanted artifacts
10	Verma *et al.* [61]	• Image resizing • Normalization	• Prepares images to meet the input requirements for the GoogleNet and ResNet-18 models	• No explicit enhancement techniques are described
11	Ouda *et al.* [44]	• Up-sampling • Cropping • Resizing • contrast	• The dataset had an uneven distribution of images across disease classes, upsampling was performed to help the model learn more effectively	• While upsampling helps balance the dataset, it can lead to overfitting by repeating minority class images, causing the model to memorize patterns instead of learning to generalize
12	Mahmoud *et al.* [68]	• Resizing to 224×224 • Normalization • Dataset splitting into 80:20 (Train, Test)	• Standard input size for CNNs ensures proper dataset division	• No additional feature enhancement
13	Ishtiaq *et al.* [60]	• Remove duplicates • Remove flow identifiers • Feature conversion • Dataset splitting • Feature normalization • Replace infinite values to 0	• Cleans data for better model performance	• May discard potentially useful data
14	Shimpi and Shanmugam [69]	• Resizing • label encoding • Data augmentation	• Standardizes input improves class balance	• No explicit enhancement techniques are described

(Contd...)

Table 2: *(Continued)*

No.	Studies	Pre-processing methods	Strengths	Weaknesses
15	Sarode and Desai [70]	• Resizing • Image enhancement (CLAHE) • Dataset splitting • Data augmentation • Normalization • Resizing to 496×496	• CLAHE enhances contrast effectively for medical images	• Computationally intensive. If parameters are not properly tuned, CLAHE can produce suboptimal results
16	Menaouer *et al.* [64]	• Average filters • Laplacian filters • Data augmentation • Dataset splitting into 80:20 (Train and Test)	• Enhances edge details, improves contrast	• Filtering may remove subtle features

CLAHE: Contrast limited adaptive histogram equalization, CNN: Convolutional neural network

(2) Feature Extraction: The Gray-Level Co-Occurrence Matrix (GLCM) approach is used to extract texture information from retinal fundus pictures.

Preprocessing the dataset was the initial stage of the suggested model [59]. To improve the quality of images, enhancement techniques are used. First, dataset images were resized (to 512 × 512) to standardize them because they have different dimensions. Then, a data augmentation method was employed to achieve data balance. To remove noise from the images, a median filter was applied to the full dataset. Finally, The sharpening filter operated by first creating a blurry copy of the original image, which was then subtracted from the original.

In addition to significant imbalance, the data also have issues with focus, exposure, noise, and artifacts. Pre-processing involved in this study [61] was resizing and normalizing the photographs to comply with GoogleNet and ResNet-18 Models' specifications for input images (224 × 224 × 3).

The authors of Abbas *et al.* [44] used a range of pre-processing methods to provide a diversity of training data. The primary method involved was upsampling the dataset for the model to learn better. After that, the dataset's images were cropped to have a 1:1 ratio size so they could be quickly and easily resized to 224 × 224. The dataset's original images included a range of resolutions. This process of cropping enables keeping the essential information to improve learning during model training.

The authors in this research [68] pre-process the Kaggle dataset by resizing images to the standard size of 224×224 pixels and performing normalization. Data was split (80/20) for training and testing was also performed.

Authors in Verma *et al.* [60] mention that data-cleaning methods such as de-noising, normalizing, and equalization can be applied to fundus images [33] to enhance image quality, as these images may include artifacts such as reflection, noise, and brightness variation. As further data augmentation approaches, flipping, rotating, and zooming can be used to reduce overfitting and diversify datasets. Pre-processing techniques can be used on the images to minimize dimensionality and enhance the effectiveness of the feature extraction and ensemble learning phases once the dataset has been cleaned, augmented, split, and labeled.

After gathering the retinal fundus images from Emma Dugas and Cukierski [33], pre-processing steps, such as scaling, cropping, and "Contrast Limited Adaptive Histogram Equalization (CLAHE)" are applied in Ali Tabtaba and Ata [42]. In the image augmentation phase, a high-quality image is provided for additional processing using Generative Adversarial Networks (GANs). Finally, the HCMD-CNN model takes the augmented images for subsequent processes. The pre-processing techniques applied in Sarode and Desai [69] were made up of 3 steps. (1) Resizing – the technique that is most commonly used for resizing to change the dimensions of images is a bilinear interpolation. (2) A technique called label encoding is applied to translate class or categorical labels into numerical representations. (3) Data augmentation – an effective pre-processing method that artificially increases the training dataset's variety. Several transformations are utilized including Rotation, Width and Height Shift, Shear Range, Zoom Range, and Horizontal Flip.

In Pin *et al.* [70], image pre-processing methods are applied before feeding OCT images to neural network models, such as resizing images to 500 × 300. After that CLAHE technique was performed to enhance the quality of images (clip limit = 2.0 and tile grid size = 3×3). There are three sets in the dataset Division. First: The dataset is randomly divided into 80% train and 20% test sets. Second K-Fold cross-validation is applied to separate the train set into five holes for training and one for validation. Finally, three sets are created from the dataset. Data augmentation was used to increase dataset size, prevent overfitting, and generalize image classification models.

This study [64] applied enhancing filters to CFP images to improve their quality and highlight the boundaries of the regions of interest. An average filter is utilized to enhance CFP images from a dataset, smoothing them and reducing noise. The Laplacian filter sharpens border delineation, making it easier to identify edges and features in the images. By employing various data augmentation techniques, including flipping, rotating, shifting, and more, the number of images during the training phase is increased. Finally, the dataset [35] is divided with an 80:20 distribution for training and testing. Table 2 lists the pre-processing methods utilized by hybrid models.

3. HYBRID DL

This section describes how the research studies were conducted. According to Bouchrika [71] the research paper's methodology is the foundation for evaluating the validity of your investigation. In this section, we discuss the methodology followed by each study chosen, and almost all of them utilize hybrid techniques for their work. Fig. 3. shows the distribution of reviewed papers published from 2019 to 2024.

This study [66] introduces a novel method for classifying 4 different categories of eye diseases using the benefits of combining CNN-RNN models (hybrid). The early stages of the methodology involve data collection from Kaggle, exploratory data analysis, pre-processing, and data transformation. In the modeling phase, CNN would serve as a feature extractor which is being carried out using the chosen transfer learning models, InceptionV3, DenseNet169, and InceptionResNetV2. The collected features are then classified using the LSTM module, which is an RNN model. The model was implemented on both imbalanced and balanced datasets. The pre-trained weights of each of the six constructed models are used in the transfer learning models. K-fold cross-validation is used to implement each of the six models at k=5.

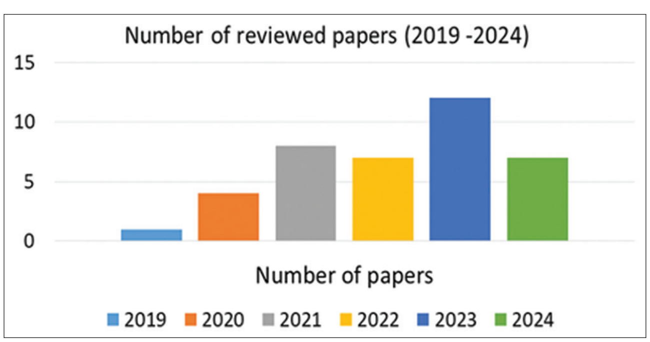

Fig. 3. Distribution of reviewed papers published per year (2019–2024).

To improve overall image quality and contrast, this paper [37] presents a hybrid image enhancement model designed specifically for CFI and five phases of early diagnosis of DR (normal, mild, moderate, severe, and PDR). The Kaggle dataset (EyePACS) and MESSIDOR were used in this article. After receiving retinal images, the model uses a modified Resnet50 network for DL feature extraction and DR classification, while also foreground detection and Gaussian blurring are used to emphasize retina vessels.

A model for multi-retinal disease classification (MRDCM) was created in this study [45]. This model utilizes a combination of ensemble, transfer, and DL techniques, focusing on the top four diseases. The process began with selecting the dataset, determining the optimal DL model, and applying data augmentation and preprocessing methods. It then employed advanced training techniques and implemented an ensemble of EfficientNetB4 and EfficientNetV2S to create the final model. The subsequent step involved interpreting the model's predictions and diagnosing images by assessing the proportion of each disease within them. For individual classifications, the researchers ultimately stacked binary logistic regression models.

The authors in Shimpi and Shanmugam [68] presented a novel hybrid model (DRNN) for DR detection and grading. It comprises two distinct innovative DL architectures, ResNet-152 and DenseNet-121. Acquiring the DR Kaggle dataset, pre-processing it by normalizing and resizing the images, dividing the training and test data in 80/20% and the applying proposed hybrid DRNN model with some hyper-parameters are the main steps of the methodology for this work. The DRNN model is constructed using many ResNet-152 layers, then multiple DenseNet-121 levels. Each layer has numerous convolution and pooling layers. The DenseNet-121 blocks extract more detailed features from the input images and the ResNet-152 blocks extract higher-level information from it. To achieve the predicted class labels, a classification layer is inserted at the network's end.

The pre-trained CNN models of GoogleNet [72] and ResNet-18 [73] are used in [61] to create a hybrid approach that extracts features from fundus images and performs binary and multiclass classifications of DR. Following the pre-processing stage, the images are sent into the transfer learning models. Both models will be used to extract a total of 1000 features. Then, four classifiers will receive the combined 2000 features as input to predict the output classes. SVM can achieve the highest percentage accuracy and other metrics in both binary and multiclass classification using hybrid features extracted from both models.

The authors of this study [62] propose a hybrid model that combines EfficientNet (for local feature extraction of the image) and Swin Transformer (to extract the global features) for the classification of DR staging. An algorithm for automated cropping of the region of interest while the image's center is kept, Gaussian blur to enhance visual clarity and contrast and additional techniques include learning rate scheduling, weight attenuation Dropout, and several data augmentation algorithms. The Model is separated into two branches: EfficientNet is used as the backbone network, while Swin Transformer is used in another branch. The two branches' outputs (extracted local features and global features) are fused through a fully connected layer after being concatenated into the classification layer for the classification of DR stages.

In Aykat and Senan [74], nine different CNN architectures are applied to the OCT retinal dataset to detect 4 retinal disease types and acquire the performance outcomes of each to detect success rates. Then, to improve these models' performance, hyper-parameter tuning is employed. Finally, based on the most effective models of these hyper-parameter tuned architectures, they created a hybrid CNN model (EfficientNetV2S and Xception) named EffXCeptNet. The proposed model was demonstrated through comparisons of the performance results with other models and outperformed them.

The authors of this study Kermany *et al.* [75] suggest a novel DL-based model for accurately predicting various eye conditions from OCT images. It is a two-step procedure that starts with segmentation using a trained U-Net model and ends with disease classification using an ensemble model made up of the Xception and InceptionV3 networks. To improve classification, the self-attention method is used to enhance model ability which makes use of each model's feature maps. The web application is built that permits users to upload their raw OCT scan pictures and obtain disease classification results for OCT images.

The automatic DR detection diagnostic tool proposed in this paper [67] named a hybrid inductive machine learning algorithm (HIMLA) that analyzes colored fundus images and classifies them as either unhealthy (having DR) or healthy (no DR). The input photos undergo pre-processing to remove any unwanted background details and improve contrast and brightness. The processed images are encoded and decoded to segment them during the segmentation stage. Based on significant information from the segmented region and how an image is altered from its original state to one afflicted by a disease, features have been extracted. Classifying retinal images using multiple instance learning (MIL) comes in the last step.

The work presented in Pin *et al.* [70] is based on an ensemble of two CNN transfer learning models. The authors propose an ensemble CNN model to analyze OCT images and classify five retinal conditions. Before feeding OCT images into neural network models, image pre-processing techniques applied, such as background removal, and contrast limited adaptive histogram equalization (CLAHE) are used to improve the quality of the images, image size reduction, and data augmentation to dataset size increasing and overfit preventing. Finally, an ensemble method based on the MobileNetV3Large [76] and ResNet50 [77] fusion probability output is suggested for achieving a more robust OCT image classification performance.

In Ishtiaq *et al.* [59] authors propose a hybrid approach for the identification and classification of DR using an ensemble-optimized CNN. The pre-processing steps include resizing images, augmenting data, median-filter applying, and sharpening images. Three approaches are utilized for feature extraction (LBP, GraphNet124, and ResNet50). Shannon Entropy algorithm is used for the selection of those features. Binary Dragonfly Algorithm [78] and Sine Cosine Algorithm (SCA) [79] are used for fusing and optimizing selected features. Ten ML algorithms are used (five of which are SVM variations and five are KNN variants), and optimized feature vectors are fed to those. Each of these algorithms was assessed using a separate evaluation matrix depicted in Table 3.

The authors in this research [57] present an innovative hybrid framework for Gl detection (Gl or non) combining CNNs (ResNet50, VGG-16) and ML (Random Forest) in an ensemble approach. The methodology consists of

Table 3: Details of chosen studies for eye disease diagnosis

Study (Year)	Dataset	Feature extraction method	Classification model	Type of classification	Accuracy (%)
Abbas *et al.* [45], 2022	• ODIR	• Convolutional layers (CNN)	• CNN	• Multi-class (4) • Two classes	• 96.9 • 100
Khan *et al.* [49], 2021	• ODIR (Kaggle)	• VGG-19	• VGG-19	• Binary classification	• 97.47
Hind Hadi *et al.* [46], 2020	• ODIR	• EfficientNet	• Custom neural network	• Multi-Label multi-class • (8 classes) Classification	• 89
Aljohani and Aburasain [58], 2022	• DRISTHI- GS • ACRIMA-DB	• HOG • GLCM	• LDA • RF • SVM • NB	• Multi-class (4)	• 73.33 • 82.56 • 82.64 • 88.86
Al-Timemy *et al.* [81], 2023	• EyeNet	• CNN	• CNN	• Multi-class (32)	• 95
Nawaz *et al.* [82], 2023	• MuReD	• DenseNet161	• C-Tran	• Multi-class (20)	-
Hossain *et al.* [39], 2023	• IDRiD • ODIR • DRISHTI-GS • Retinal Dataset-GitHub • Messidor • Messidor-2	• ResNet50 • VGG-16 • Xception • EfficientNetB7 • Custom DCNN model	• ResNet50 • VGG-16 • Xception • EfficientNetB7 • Custom DCNN model	• Multi-class (4)	• 96.94
Hossain *et al.* [50], 2024	• DIARETDB0 • DIARETDB1 • Messidor • HEI-MED • ODIR (Kaggle) • Retina	• EfficientNetB0 • VGG16 • ResNet152V2 • GRU+ResNet152V2 • Bi-GRU+ResNet152V2	• EfficientNetB0 • VGG16 • ResNet152V2 • GRU+ResNet152V2 • Bi-GRU+ResNet152V2	• Multi-class (4)	• 98.76 • 98.11 • 97.3 • 98.38 • 98.11
Hossain *et al.* [55], 2020	• STARE	• CNN (AlexNet)	• CNN (AlexNet)	• Multi-class (4)	-
Hossain *et al.* [38], 2020	• Private • HRF • DRIVE • STARE • IDRiD	• DCNN (AlexNet)	• DCNN (AlexNet)	• Binary classification	• 95.77
Vadduri and Kuppusamy [40], 2021	• ORIGA • IDRiD • MESSIDOR • ARIA • STARE	• ResNets • VGGs	• DNN	• Multi-class (4)	• 85.79
Rodríguez *et al.* [83], 2021	• Kaggle	• MobileNetV2	• MobileNetV2 • (Transfer learning)	• Multi-class (5)	• 96.2
Wang *et al.* [47], 2021	• ODIR	• Resnet-34 • EfficientNet • MobileNetV2 • VGG-16	• Resnet-34 • EfficientNet • MobileNetV2 • VGG-16	• Multi-class (8)	• 90.85 • 94.32 • 93.82 • 97.23
Dipu *et al.* [48], 2022	• ODIR	• VGG-19	• VGG-19	• Binary classification	• 94.0 • 88.9 • 86.1 • 86.6 • 98.1 • 90.9 • 86.8
Ali Tabtaba and Ata [43], 2022	• RFMiD	• ML-CNN	• ML-CNN • (sigmoid)	• Multi-class (45)	• 94.3
Vanita Sharon and Saranya [56], 2023	• DRISTHI-GS1 ORIGA	• DNN • (SqueezeNet)	• KNN • SVM • DT • RF • NB • LR	• Binary classification	• 65.3–99

(Contd...)

Table 3: ***(Continued)***

Study (Year)	Dataset	Feature extraction method	Classification model	Type of classification	Accuracy (%)
Chea and Nam [41], 2023	• IDRiD • HRF • ODIR • RFMiD	• CNN • Transfer learning (EfficientNet)	• CNN • Transfer learning	• Multi-class (4)	• 84 • 94
Albelaihi and Ibrahim [51], 2021	• Messidor • Messidor-2 • DRISHTI-GS • Kaggle	• CNN	• CNN	• Multi-class (4)	• 81.33
Sarki *et al.* [52], 2019	• Messidor	• AlexNet • VGG-16 • SqueezeNet • Custom CNN	• AlexNet • VGG-16 • SqueezeNet • Custom CNN	• Binary classification	• 93.46 • 91.82 • 94.49 • 98.15
Guo *et al.* [84], 2020	• Kaggle	• CNN • (AlexNet)	• CNN • (AlexNet)	• Binary classification	• 88.13 • 73.75 • 89.38 • 86.88 • 97.50

DRIVE: Digital retinal images for vessel extraction, IDRiD: Indian DR image dataset, HRF: High-resolution fundus, STARE: Structured analysis of the retina, RFMiD: Retinal fundus multi-disease image dataset, ODIR: Ocular disease intelligent recognition, ORIGA: Online retinal fundus image dataset for Gl analysis and research, DIARETDB0: Standard DR database calibration level 0, DIARETDB1: Standard DR database calibration level 1, ARIA: Automatic retinal image analysis, APTOS-2019: Asia Pacific Tele-Ophthalmology Society 2019, LDA: Linear discriminant analysis, CNN: Convolutional neural network, DCNN: Deep: Convolutional neural network, Messidor: Methods to evaluate segmentation and indexing techniques in the field of retinal ophthalmology, Messidor-2: Methods to evaluate segmentation and indexing techniques in the field of retinal ophthalmology-version 2

four main steps including data collection, pre-processing (converting images to gray-scale and texture extraction), training 3 models, and classification. GLCM was used to extract texture features, which were then fed into the Random Forest algorithm. Moreover, retinal grayscale fundus have been fed into the ResNet50 and VGG16 models. By using ensemble modeling (combining 3 models), the Gl detection framework was carefully created.

In Al-Timemy *et al.* [80] authors developed a hybrid DL model to detect keratoconus (KCN) based on corneal maps. To identify KCN-induced lesions associated with a specific corneal map exclusively, they first created seven DL models based on the EfficientNet-b0 architecture, each of which was trained to extract deep features from that map. Next, deep features from various corneal maps are combined to create a hybrid model that combines deep features (1000) extracted from each corneal map based on a support vector machine to generate a concatenated vector with 7000 deep features.

To classify fundus images for 3 disease types, this study [60] uses a hybrid approach that combines ensemble learning and deep-trained feature extraction models. After some pre-processing methods, this study used 8 DL pre-trained models for feature extraction and applied 3 ensemble learning models (Extra Trees, Histogram Gradient Boosting, and Random Forest) for classification. The results showed that the combination of DenseNet for feature extraction and ensemble learning models (classifiers) produced the best results and outperformed other techniques and classifiers. To precisely predict the risk of diabetes at an early stage, a novel Hybrid CNN and Autoencoder model is presented in this paper [69]. The methodology taken by the authors includes data collection, pre-processing (Image Resizing, Label encoding, and Data Augmentation), and Proposing a hybrid model of CNN and autoencoder. The CNN is used to extract spatial features from the retinal images, while Autoencoder is used for unsupervised feature learning and dimensionality reduction, by combining the advantageous characteristics of both a hybrid model is designed.

This study [53] proposed a hybrid DL-metaheuristic model for automated diagnosis of DR. An InceptionV3 DL model, is used for feature extraction from fundus images. Simulated Annealing (SA) is applied in the feature selection process. The proposed model has four steps. (1) Retinal image pre-processing. (2) In the feature extraction step, processed images are fed into a deep CNN network and abstract features are obtained using the transfer learning approach. (3) In the feature selection step, a metaheuristic algorithm (i.e., SA) is applied to reduce the number of features while obtaining the best potential features. (4) A decision tree-based algorithm (XGBoost) which is an ensemble method is used as a classifier.

Another research [36] proposed a hybrid feature extraction method for 4 types of eye disease classification. Pre-processing tasks include ROI Extraction and image resizing to a standardized size. Feature extraction is done by utilizing 3 methods (LBP, GLCM, and TFCM). Then, those features are combined into a single feature vector, representing the texture and statistical features of the eye disorders. Finally, the two classifiers were utilized for classification (kNN and SVM).

A DR diagnosis model is proposed in Ali Tabtaba and Ata [42], in which fundus images are taken from 3 datasets. The pre-processing tasks were done including scaling, cropping, and CLAHE. When image augmentation is performed, high-quality images are provided for additional processing carried out by GANs. The augmented photos are subsequently fed into a hybrid cascaded multi-scale Dilated CNN model (HCMD-CNN), whereby the MobileNet and Residual Attention Network are used to produce a promising result. By suggesting the novel algorithm called MSTGEO, the hyper-parameters in the network were optimally selected.

The authors of this research [63] propose a hybrid DL strategy for the identification and classification of DR, utilizing two VGG network models (VGG16 and VGG19) in conjunction with the deep CNN method. First images were pre-processed and then CNN and two VGG NETWORK models were used for feature extraction and classify the data.

The goal of this work [64] is to apply hybrid strategies based on feature extraction and fusion methods to classify an eye disease dataset. The first approach uses an ANN to classify fundus images utilizing features from the DenseNet121 and MobileNet models independently after using principal component analysis to reduce the high dimensionality and repetitive features. The second approach uses ANN based on fused features from the MobileNet and DenseNet121 models, both before and after feature reduction. The third approach uses ANN to categorize the eye illness dataset using hand-crafted features and fused features from the MobileNet and DenseNet121 models separately. The ANN achieved the highest accuracy by combining handcrafted features with a fused MobileNet.

4. DISCUSSION AND FUTURE WORK

The primary aim of this research is to present a comprehensive review of hybrid models form an important aspect of DL-based system analysis of retinal fundus images. A hybrid model due to the integration of different methods used to diagnose eye diseases.

A summary and discussion of the performances of chosen schemes are provided in this section. ML and DL-based approaches for eye disease identification and classification using retinal images are shown in Table 3, and hybrid-based approaches are depicted in Table 4. The accuracy ranges of ML/DL studies vary between 73% and 98%. The maximum accuracy was 98.76% achieved by Albelaihi and Ibrahim [50]. In which authors proposed a model called "DeepDiabetic" for diagnosing and identifying four different types of diabetic eye diseases, they considered five architectures' performances, and the EfficientNetB0 model did better than the other five which achieved high accuracy. The minimum accuracy was obtained by Nawaldgi and Lalitha [58]. In this proposed work, structural (CDR and RDR) and textural (HOG and GLCM) features are used to develop an automated Gl assessment approach from CFI. Among four Classifiers utilized for the classification task Linear Discriminant Analysis achieved the lowest accuracy (73.33%).

It is a noteworthy achievement to use DL models to analyze retinal fundus images with over 90% accuracy. Among the studies, many methods achieved an accuracy of over 90%, including those reported from [36-39], [41-45], [47], [49,50], [52,53], [57], [59], [63,64], [67-70], [74], [81], [83], and [85]. In contrast, others achieved lower than 90% accuracy, including [40], [46], [51], [58], [60], [66], and [80]. See Table 4, in some of those studies, the authors' focus was on using traditional ML feature extraction methods [58]. However, these might not be sufficient to capture the full complexity of the data when compared with DL-based approaches which are the most commonly used to date. The pre-processing step enhances the effectiveness of DL approaches, especially in analyzing medical images. If the pre-processing stages do not handle imbalanced datasets, image quality enhancement, noise reduction, and other standards used in image pre-processing analysis the model might perform well on the majority of diagnoses but lead to poor feature extraction and fail to detect rare retinal abnormalities. Furthermore, relying on only a single or small dataset might restrict the model's generalization to other datasets or real-world clinical data. Data augmentation can be used to increase the amount of samples. Thus, taking these problems into account will significantly enhance the model's performance.

Table 4 demonstrates hybrid-based methodologies built for eye disease identification and classification using retinal

Table 4: Details of hybrid studies for eye disease diagnosis

Study (Year)	Dataset	Feature extraction method	Classification model	Type of classification	Performance (%)
Doddi *et al.* [36], 2023	• Kaggle (eye disease classification)	• LBP • GLCM • TFCM	• SVM • KNN	• Multi-class (4)	• 99.88 • 99.55
Abbood *et al.* [37], 2024	• Kaggle (EyePACS) • Messidor	• ResNet50	• ResNet50	• Multi-class (5)	• 92
Retina Dataset [66] 2021	• Kaggle	• (CNN) • InceptionV3 • InceptionResNetV2 • DenseNet169	• (RNN) • LSTM	• Multi-class (4)	• 69.50
Khan *et al.* [53] 2023	• Messidor-2	• InceptionV3 • Simulated Annealing	• XGBoost	• Binary classification	• 92.55
Butt *et al.* [62] 2024	• Kaggle • (APTOS-2019)	• EfficientNet • Swin Transformer	• Hybrid model	• Multi-class (5)	• 97
Xu *et al.* [63] 2022	• Kaggle (APTOS-2019)	• CNN • VGG16 • VGG19	• CNN • VGG16 • VGG19	• Multi-class (5)	• 90.60
Londhe [67] 2023	• CHASE	• Optimization of attributes	• Multiple instance learning	• Binary classification	• 96.62
Thanki [57] 2024	• ACRIMA • G1020 • ORIGA • REFUGE	• GLCM	• Random Forest • ResNet50 • VGG16	• Binary classification	• 95.41
Nawaldgi and Lalitha [59] 2023	• Kaggle (EyePACS)	• LBP • GraphNet124 • ResNet50	• SVM • KNN	• Multi-class (5)	• 98.85
Verma *et al.* [61] 2022	• Kaggle (APTOS-2019)	• (Transfer learning) • GoogleNet • ResNet-18	• NB • RF • RBF • SVM	• Binary • Multi-class (3)	• 97.80 • 89.29
Ouda *et al.* [44] 2022	• RFMiD	• EfficientNetB4 • EfficientNetV2S	• Ensemble learning	• Multi-class (4)	• 96.23
Mahmoud *et al.* [68] 2023	• Kaggle	• ResNet-152 • DenseNet-121	• Hybrid model (DRNN)	• Multi-class (27)	• 96.91
Ishtiaq *et al.* [60] 2024	• Kaggle (EyePACS)	• DenseNet201 • InceptionResNetv2 • MobileNetV2 • ReseNet152V2 • NASNetMobile • NASNetLarge • VGG16 • VGG19	• Random Forest • Extra Tree • Histogram Gradient	• Multi-class (3)	• 87.2
Shimpi and Shanmugam [69] 2024	• Private	• CNN • Autoencoder	• CNN • Autoencoder	• Multi-class (5)	• 90.92
Sarode and Desai [70] 2021	• Private	• MobileNetV3Large • ResNet50	• Ensemble model • (CNN)	• Multi-class (5)	• 91.69
Menaouer *et al.* [64] 2023	• Kaggle (eye disease classification)	• DenseNet-121 • MobileNet	• ANN	• Multi-class (4)	• 98.5
He *et al.* [74] 2023	• OCT	• EfficientNetV2S • Xception	• Hybrid model • (EffXCeptNet)	• Multi-class (5)	• 99.90
Syarifah *et al.* [85] 2024	• Public	• InceptionV3 • Xception	• Ensemble model	• Multi-class (4)	• 96.60
Mirjalili [80] 2021	• Private	• (Hybrid model) • EfficientNetB0	• SVM	• Multi-class (5)	• 81.6
Babaqi *et al.* [42] 2024	• IDRiD • DIARETDB1 • Messidor-2	• MobileNet • Residual Attention Network	• MSTGEO-HCMD-CNN	• Multi-class (5)	• 95.79

RFMiD: Retinal fundus multi-disease image dataset, ODIR: Ocular disease intelligent recognition, ORIGA: Online retinal fundus image dataset for Gl analysis and research, REFUGE: Retinal fundus Gl challenge, APTOS-2019: Asia Pacific Tele-Ophthalmology Society 2019, CNN: Convolutional neural network, Messidor: Methods to evaluate segmentation and indexing techniques in the field of retinal ophthalmology, Messidor-2: Methods to evaluate segmentation and indexing techniques in the field of retinal ophthalmology-version 2, GLCM: Gray-Level Co-Occurrence Matrix images and OCT images. The obtained accuracy of the proposed hybrid-based models ranges from 69% to 99%. The highest accuracy belongs to Aykat and Senan [74] which is 99.9%, and 69.5% of Londhe [66] is the lowest accuracy of all the chosen classification techniques.

Similarly, in terms of sensitivity (True Positive Rate or Recall) as shown in Fig. 4, the maximum obtained sensitivity scores among all of the chosen researches is 99.9% of Aykat and Senan [74], and the minimum one is 69.5% which belongs to Londhe [66]. A sensitivity score of above 90% was attained in certain works, including [36], [42], [59], [61], [62], [67], [68], [70], [74], [85] and [63], while others reported sensitivity below 90%. In addition, some researches scored sensitivity up to 95%, such as [61] (binary classification), [36], [59], [67], [74], [85] and [42] as shown in Fig. 5.

Regarding acquiring precision scores for chosen researchers, they range from 89.40 % to 99.9%. The study [74] scored the highest precision rate of 99.9% in which they built a hybrid CNN model named EffXCeptNet (combined EfficientNetV2S and Xception), authors applied nine different CNN architectures on OCT retinal dataset to detect 4 retinal disease types. The pre-trained CNN models of GoogleNet and ResNet-18 are used in Butt *et al.* [61] to propose a hybrid approach that extracts features from fundus images and performs binary and multiclass classifications of DR. However, their binary classification achieved a 97.8% precision rate but the multiclass classification achieved the lowest precision rate of 89.40% among all other studies where chosen.

Fig. 6. shows the distribution of papers published from 2019 to 2024. The number of published studies related to retinal diseases was retrieved from PubMed [86]. The number of publications in this field has steadily increased over the years, reflecting the growing interest and advancements in DL applications for fundus image analysis. Notably, the number of studies rose from 13 in 2019 to 73 in 2024, demonstrating an accelerating research focus in this area. The trend suggests that research interest peaked in 2024, likely due to advancements in DL techniques including hybrid approaches and the availability of large-scale datasets.

The most commonly used datasets in retinal disease diagnosis studies are shown in Fig. 7. The findings reveal that Messidor and EyePACS are the most frequently utilized datasets. This is likely because these datasets are widely used in DR diagnosis, which remains a primary focus in retinal disease research due to its high global prevalence. ORIGA is also widely used; it was specifically developed for Gl diagnosis and OD/OC segmentation. The IDRiD dataset was created to assess the severity of DR and DME. It stands out for its high-quality annotations, making it a valuable resource for accurate disease grading and analysis.

Moderately used datasets, such as ODIR and DRIVE, are often chosen for specific diagnostic tasks such as multi-disease classification and Vessel Extraction. On the other hand, RFMiD and HRF are used less frequently in studies, as researchers often prefer datasets that better suit their specific research goals and offer larger sample sizes. These findings highlight a strong preference for large, well-annotated datasets, which are essential for effectively training and

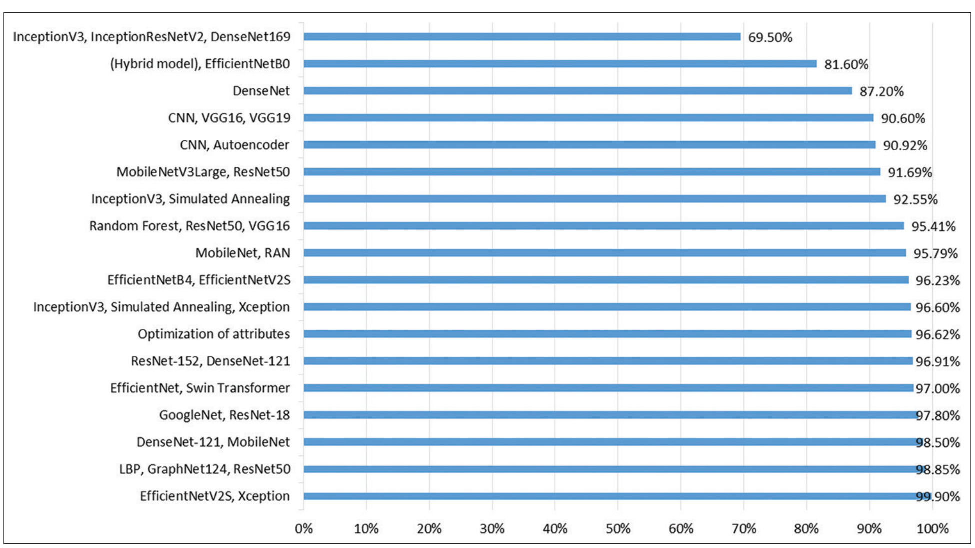

Fig. 4. The effect of hybrid deep learning on performance.

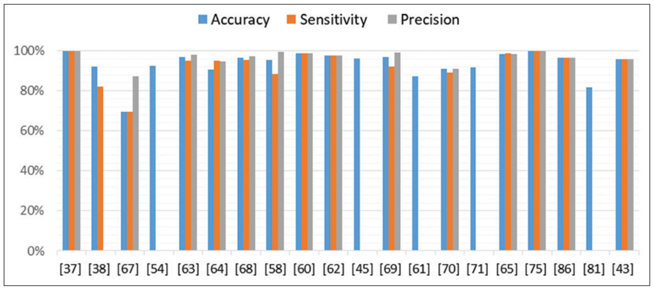

Fig. 5. Accuracy, sensitivity and precision for hybrid deep learning models.

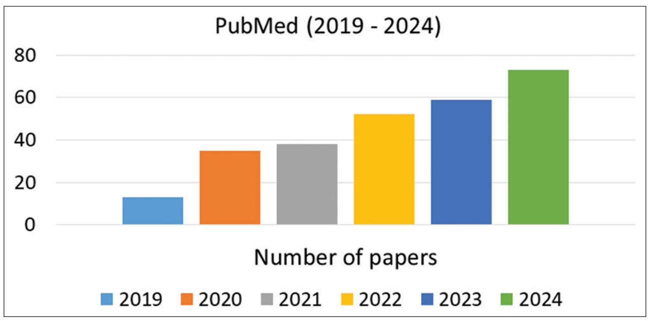

Fig. 6. Number of papers published per year (2019–2024).

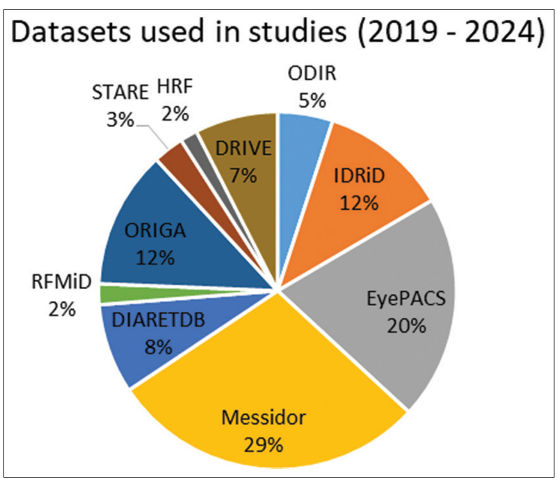

Fig. 7. Percentage of datasets used in papers (2019–2024).

validating DL models in this field. However, the limited use of certain datasets suggests they may be underutilized, which could be addressed in future research to improve dataset diversity and enhance model generalization.

Although the use of DL in fundus image analysis has produced excellent outcomes, it is important to remember that there are still many other areas in which it is still limited. After reviewing various learning-based techniques for the detection and classification of eye diseases, the following outlines their advantages, and limitations of recent studies.

Certain studies primarily focus on performing fundus image detection or classification of one type of eye disease alongside normal (healthy) cases [38], [48], [49], [52], [56], [84], for example, the presence or absence of DR or CAs, that is, binary classification. Exploring the scope to deal with a wider range of conditions could enhance the model's applicability and make it more versatile for real-world clinical use. The process of Disease detection/classification expanded in Ouda *et al.* [43], Wang *et al.* [46], Dipu *et al.* [47], Retina_Dataset [68], Rodríguez *et al.* [82] by considering some other types of Diabetic eye diseases including AMD, CAs, myopia and more. Expanding to contain diverse diseases can elevate the quality of their work much more and make it more impactful and applicable in real-world scenarios. While some datasets have Fundus images with labeling stages of some diseases which can be considered for eye disease detection and severity grading (e.g., mild, moderate, and severe), in this way the studies conducted in Hossain *et al.* [38], Khan *et al.* [49], Khan *et al.* [52], Thanki [56] are significantly enhanced as it enables the system to detect the diseases at earlier stages. The performance of models can be improved by focusing on more practical solutions to address the class imbalance issue present in the suggested datasets, which still needs further attention in several studies [43], [46], [56], [82], [83].

Some studies only utilize a single CNN architecture [49], comparisons with other models or previous researches are not given [51], [55], [84], while it might add significant value to the research. It might be more useful for Nawaz *et al.* [81], Guo *et al.* [83] to compare their approach with a wider range of state-of-art models to highlight the strengths/weaknesses of the proposed approach and could provide more insights for researchers about various models' strengths and effectiveness. While also essential for enriching findings and showing how your work is better and differs from others.

Researchers make use of both ML [36], [58] and DL models for eye disease diagnosis. Each approach offers unique advantages, but DL-based models could be used in Thanki [56], Nawaldgi and Lalitha [58] to automatically extract features and improve classification tasks. In addition, it has shown great success in tasks such as image analysis, particularly in medical image classification.

When datasets have a limited number of samples which is considered low, this might raise the risk of overfitting and class imbalance. Therefore, studies like [42], [59], [64] have applied strategies to increase fundus images, such as data augmentation to balance the data and DL models to generalize to any new datasets as a large number of samples are required during the training phase. Some studies [46], [55], [83] rely only on a single and small dataset which might increase the restriction of the model's generalization on other datasets or real-world clinical data. On the other hand, studies like [42], [57] evaluated their mode with more than one dataset.

The pre-processing stage is an essential section in research papers because of the details of how raw data in datasets are prepared for feature extraction and training of the models. However, several studies, including [38], [41], [56], [58] do not provide detailed information about pre-processing of dataset images such as how they deal with dataset imbalance, image cleaning, normalization, data augmentation, resizing, and more.

Future work is an important part of research sections that contain valuable information about some works that are missed currently and new ideas that might be considered in future work. Some researchers do not suggest any additional or alternative approaches that might be explored in future research, such as [47], [52].

Some studies [47], [56] seek to classify different types of ocular diseases but they do not provide a brief overview of the various types of ocular diseases that they tried to detect, which might be useful for readers to obtain basic information about them to realize how normal images are different from abnormal ones and which portion of the image is important to determine the exact disease.

To evaluate the effectiveness of the models, it is essential to provide details of performance metrics such as accuracy, precision, recall, and others. The absence of showcasing these metrics, as observed in Vanita Sharon and Saranya [55], leaves the readers without a clear understanding of how well the model performs.

As observed in recent studies, a key trend in this field is the recent advancements of a synthesis of the most recent transfer, ensemble, and DL techniques that are significantly utilized to create an accurate, reliable model for eye disease diagnosis; this could potentially increase accuracy and capacity of predictions. More especially, hybrid DL models offer stronger feature extraction capabilities, making them highly effective for complex classification tasks. Another trend is the transition from single-disease detection to multi-disease classification and severity grading that enables early detection and supports efforts for widespread screening.

Future research should focus on offering an AI-automated tool (Real-time implementation) for diagnosing disorders related to the eyes that experts in medical departments can use. It is desperately needed in clinical centers and serves as an Internet of Medical Things (IoMT) application. This strategy helps with the early referral of emergency patients to specialists and may reduce the time needed for clinical diagnosis.

In addition, expanding the dataset's size or combining several different datasets to increase the number and include a more varied sample of demographics, nationalities, and geographic regions builds a more precise or enhances the model's resilience and generalizability.

5. CONCLUSIONS

This paper proposed a concise review of introducing a range of learning paradigms including DL, hybrid, and ensemble models utilized for the purpose of diagnosis of eye diseases. More specifically, this review focused on one type of ophthalmic imaging modality, which includes an extensive range of disorders relating to the eyes in image format, that is, fundus images. In addition, highlights the advantages of hybrid techniques that integrate different machine learning and DL algorithms with required image processing methods to detect, diagnose, classify, and grading various retinal diseases. A survey of the selected papers was conducted over the past 5 years; here we narrowed down the review of studies conducted in 2019. We described and summarized the methodologies of selected studies in the area of fundus image diagnosis, including data collection, pre-processing approaches, feature extraction, and classification models. According to our analysis of these studies, hybrid techniques have been widely utilized by researchers for the purpose of combining the strengths of different models, enhancing diagnostic accuracy, and improving feature extraction and classification.

In addition, we have noted a number of restrictions related to the investigations. We have discussed their advantages, challenges, emerging trends, and potential opportunities for future research in this field. Furthermore, we highlighted the strengths and weaknesses of the most commonly used datasets in these studies. As we realized AI systems can help physicians by offering an automated tool for the early identification, classification, and grading of various eye conditions. Given the lack of medical specialists relative to the number of patients, offering a cost-effective automated AI system for diagnosing disorders related to the eyes is desperately needed, which helps support medical professionals and allows patients to begin treatment sooner. We hope that our research will be able to provide an in-depth analysis and cover a thorough and up-to-date summary of Eye disease diagnosis.

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REFERENCES

[1] WHO. "Blindness and vision impairment." World Health Organization. Available from: https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment [Last accessed on 2024 Aug 21].

[2] D. Bordoloi, V. Singh, S. Sanober, S. M. Buhari, J. A. Ujjan and R. Boddu, "[Retracted] Deep learning in healthcare system for quality of service," *Journal of Healthcare Engineering,* vol. 2022, no. 1, p. 8169203, 2022.

[3] G. A. Saleh, N. M. Batouty, S. Haggag, A. Elnakib, F. Khalifa, F. Taher, M. A. Mohamed, R. Farag, H. Sandhu, A. Sewelam and A. El-Baz, "The role of medical image modalities and AI in the early detection, diagnosis and grading of retinal diseases: A survey," *Bioengineering,* vol. 9, no. 8, p. 366, 2022.

[4] ophthalmology.med.ubc.ca. "*Color Fundus Photography*," Available from: https://ophthalmology.med.ubc.ca/patient-care/ophthalmic-photography/color-fundus-photography [Last accessed on 2024 Aug 21].

[5] The University of British Columbia. "*Ophthalmology Fundus Image*," Available from: https://ophthalmology.med.ubc.ca/files/2013/11/img-03.jpg [Last accessed on 2025 Feb 11].

[6] M. Mateen, J. Wen, Nasrullah, S. Song and Z. Huang, "Fundus image classification using VGG-19 architecture with PCA and SVD," *Symmetry,* vol. 11, no. 1, p. 1, 2018.

[7] D. Neely. "*Diabetic Retinopathy: Causes, Symptoms, Treatment*," Available from: https://www.orbis.org/en/avoidable-blindness/diabetic-retinopathy?psafe_param=1&gad_source=1&gclid=EAIaIQobChMI4JrP_KCIiAMV0hEGAB1tiA5xEAAYASAAEgLM2fD_BwE [Last accessed on 2024 Aug 22].

[8] "*Glaucoma Overview*," Available from: https://www.nhs.uk/conditions/glaucoma/#:~:text=Glaucoma%20is%20a%20common%20eye,not%20diagnosed%20and%20treated%20early [Last accessed on 2024 Aug 22].

[9] K. Boyd. "*What Are Cataracts?*" American Academy of Ophthalmology. Available from: https://www.aao.org/eye-health/diseases/what-are-cataracts [Last accessed on 2024 Aug 22].

[10] D. Turbert. "*Nearsightedness: What Is Myopia*?" American Academy of Ophthalmology. Available from: https://www.aao.org/eye-health/diseases/myopia-nearsightedness [Last accessed on 2024 Aug 22].

[11] K. Boyd, "*What Is Macular Degeneration*?" American Academy of Ophthalmology. Available from: https://www.aao.org/eye-health/diseases/amd-macular-degeneration [Last accessed on 2024 Aug 22].

[12] P. Porwal, S. Pachade, R. Kamble, M. Kokare, G. Deshmukh, V. Sahasrabuddhe and F. Meriaudeau, "Indian diabetic retinopathy image dataset (IDRiD): A database for diabetic retinopathy screening research," *Data,* vol. 3, no. 3, p. 25, 2018.

[13] A. Budai, R. Bock, A. Maier, J. Hornegger and G. Michelson, "(HRF) Robust vessel segmentation in fundus images," *International Journal of Biomedical Imaging,* vol. 2013, no. 1, p. 154860, 2013.

[14] A. Budai and J. Odstrcilik, *"High-Resolution Fundus (HRF) Image Database*." Pattern Recognition Lab, FAU. Available from: https://www5.cs.fau.de/research/data/fundus-images [Last accessed on 2025 Feb 09].

[15] E. Decencière, X. Zhang, G. Cazuguel, B, Laÿ,…& J. C. Klein, "Feedback on a publicly distributed image database: The messidor database," *Image Analysis and Stereology,* vol. 33, pp. 231-234, 2014.

[16] ADCIS. "*Messidor: A Retinopathy Dataset*." Available from: https://www.adcis.net/en/third-party/messidor [Last accessed on 2025 Feb 09].

[17] J. Staal, M. D. Abramoff, M. Niemeijer, M. A. Viergever and B. V. Ginneken, " Ridge-based vessel segmentation in color images of the retina," *IEEE Transactions on Medical Imaging*, vol. 23, no. 4, pp. 501-509, 2004.

[18] "*STARE: A Retinal Image Dataset*." Available from: http://cecas.clemson.edu/~ahoover/stare [Last accessed on 2025 Feb 09].

[19] S. Pachade, P. Porwal, D. Thulkar, M. Kokare, G. Deshmukh, V. Sahasrabuddhe, L. Giancardo, G. Quellec and F. Mériaudeau, "Retinal fundus multi-disease image dataset (RFMiD): A dataset for multi-disease detection research," *Data,* vol. 6, no. 2, p. 14, 2021.

[20] I. Dataport. "*Retinal Fundus Multi-Disease Image Dataset (RFMID)*," Available from: https://ieee-dataport.org/open-access/retinal-fundus-multi-disease-image-dataset-rfmid [Last accessed on 2025 Feb 09].

[21] "*International Competition on Ocular Disease Intelligent Recognition,*" Available from: https://odir2019.grand-challenge.org/dataset [Last accessed on 2024 Aug 31].

[22] "*Ocular Disease Recognition*," Available from: https://www.kaggle.com/datasets/andrewmvd/ocular-disease-recognition-odir5k [Last accessed on 2024 Aug 31].

[23] "*Messidor2: A Retinopathy Dataset*," Available from: https://www.adcis.net/en/third-party/messidor2 [Last accessed on 2025 Feb 09].

[24] Z. Zhang, F. S. Yin, J. Liu, W. K. Wong, N. M. Tan, B. H. Lee, J. Cheng and T. Y. Wong, "ORIGA(-light): an online retinal fundus image database for glaucoma analysis and research," *Annual International Conference of the IEEE Engineering in Medicine and Biology,* vol. 2010, pp. 3065-3068, 2010.

[25] J. I. Orlando, H. Fu, J. B. Breda, K. van Keer, D. R. Bathula, A. Diaz-Pinto.,& H. Bogunović, REFUGE Challenge: A unified framework for evaluating automated methods for glaucoma assessment from fundus photographs," *Medical Image Analysis,*

vol. 59, p. 101570, 2020.

[26] *R. Challenge. " REFUGE: Retinal Fundus Glaucoma Challenge*," Available from: https://refuge.grand-challenge.org [Last accessed on 2025 Feb 09].

[27] [27] T. Kauppi, V. Kalesnykiene, J.K. Kamarainen, L. Lensu, I. Sorri, H Uusitalo, H. Kalviainen and J. Pietila, "*DIARETDB 0: Evaluation Database and Methodology for Diabetic Retinopathy Algorithms*," 2007.

[28] "*DIARETDB0: A Database for Diabetic Retinopathy*," LUT University. Available from: https://www.it.lut.fi/project/imageret/diaretdb0 [Last accessed on 2025 Feb 09].

[29] [29] T. Kauppi, V. Kalesnykiene, J.K. Kamarainen, L. Lensu, I. Sorri, A. Raninen, R. Voutilainen, H Uusitalo, H. Kalviainen and J. Pietila, "The DIARETDB1 Diabetic Retinopathy Database and Evaluation Protocol. In" "*British Machine Vision Conference*," 2007.

[30] J. Sivaswamy, S. R. Krishnadas, G. D. Joshi, M. Jain and A. U. S. Tabish, "Drishti-GS: Retinal Image Dataset For Optic Nerve Head (ONH) Segmentation. In: "*2014 IEEE 11th International Symposium on Biomedical Imaging (ISBI)*," pp. 53-56, 2014.

[31] "*Drishti-GS: Glaucoma Dataset*." CVIT, IIIT Hyderabad. Available from: http://cvit.iiit.ac.in/projects/mip/drishti-gs/mip-dataset2/Home.php [Last accessed on 2025 Feb 10].

[32] J. Sivaswamy, A. Chakravarty, G. D. Joshi and T. A. Syed, *"(Drishti-GS1)A Comprehensive Retinal Image Dataset for the Assessment of Glaucoma from the Optic Nerve Head Analysis*," [Working Paper], 2015.

[33] J. Emma Dugas, W. Cukierski, "*Diabetic Retinopathy Detection*." Available from: https://www.kaggle.com/c/diabetic-retinopathy-detection/data [Last accessed on 2024 Sep 02].

[34] Kaggle, "*APTOS-2019 Dataset*," Available from: https://www.kaggle.com/datasets/mariaherrerot/aptos2019 [Last accessed on 2024 Sep 02].

[35] G. V. Doddi. Available from: https://www.kaggle.com/datasets/gunavenkatdoddi/eye-diseases-classification/data [Last accessed on 2024 Feb 09].

[36] S. Abd Kadum, F. H. Najjar, H. M. Al-Jawahry, and F. Mohamed, Eye Diseases Classification Based on Hybrid Feature Extraction Methods. In: "*2023 6th International Conference On Engineering Technology and Its Applications (IICETA)*,"IEEE, United States, pp. 402-407, 2023.

[37] [37] S. H. Abbood, H. N. A. Hamed, M. S. M. Rahim, A. Rehman, T. Saba, and S. A. Bahaj, "Hybrid Retinal Image Enhancement Algorithm for Diabetic Retinopathy Diagnostic Using Deep Learning Model," *IEEE Access*, vol. 10, pp. 73079-73086, 2022.

[38] M. R. Hossain, S. Afroze, N. Siddique and M. M. Hoque, "Automatic Detection of Eye Cataract Using Deep Convolution Neural Networks (DCNNs). In: *2020 IEEE Region 10 Symposium (TENSYMP)*, IEEE, United States, pp. 1333-1338, 2020.

[39] M. Vadduri and P. Kuppusamy, "Enhancing ocular healthcare: Deep learning-based multi-class diabetic eye disease segmentation and classification," *IEEE Access,* vol. 99, p. 1, 2023.

[40] N. Chea and Y. Nam, "Classification of fundus images based on deep learning for detecting eye diseases," *Computers, Materials and Continua,* vol. 67, no. 1, pp. 411-426, 2021.

[41] T. Babaqi, M. Jaradat, A. E. Yildirim, S. H. Al-Nimer and D. Won, "Eye Disease Classification Using Deep Learning Techniques," *arXiv preprint arXiv:2307.10501,* 2023.

[42] A. Ali Tabtaba and O. Ata, "Diabetic retinopathy detection using developed hybrid cascaded multi-scale DCNN with hybrid heuristic strategy," *Biomedical Signal Processing and Control,* vol. 89, p. 105718, 2024.

[43] O. Ouda, E. AbdelMaksoud, A. Abd El-Aziz and M. Elmogy, "Multiple ocular disease diagnosis using fundus images based on multi-label deep learning classification," *Electronics,* vol. 11, no. 13, p. 1966, 2022.

[44] R. Abbas, S. O. Gilani and A. Waris, "Ensemble Based Multi-Retinal Disease Classification and Application with Rfmid Dataset Using Deep Learning," *SSRN Journal [Preprint]*, 2022.

[45] A. Hind Hadi, A. S. Ali Yakoob and H. Enass, "Classifying three stages of cataract disease using CNN," *Journal of University of Babylon,* vol. 30, no. 3, pp. 150-167, 2022.

[46] J. Wang, L. Yang, Z. Huo, W. He and J. Luo, "Multi-label classification of fundus images with efficientNet," *IEEE Access,* vol. 8, pp. 212499-212508, 2020.

[47] N. M. Dipu, S. A. Shohan and K. Salam, "Ocular disease detection using advanced neural network based classification algorithms," *Asian Journal For Convergence In Technology (AJCT)*, vol. 7, no. 2, pp. 91-99, 2021.

[48] M. S. Khan., N. Tafshir, K. N. Alam, A. R. Dhruba, M. M. Khan, A. A. Albraikan, F. A. Almalki, "Deep learning for ocular disease recognition: An inner-class balance," *Computational Intelligence and Neuroscience,* vol. 2022, p. 5007111, 2022.

[49] M. S. M. Khan, M. Ahmed, R. Z. Rasel and M. M. Khan, Cataract Detection Using Convolutional Neural Network with VGG-19 Model. In: "*2021 IEEE World AI IoT Congress (AIIoT)*," pp. 209-212, 2021.

[50] A. Albelaihi and D. M. Ibrahim, "Deep diabetic: An identification system of diabetic eye diseases using deep neural networks," *IEEE Access*, vol. 12, pp. 10769-10789, 2024.

[51] R. Sarki, K. Ahmed, H. Wang, Y. Zhang and K. Wang, "Convolutional neural network for multi-class classification of diabetic eye disease," *EAI Endorsed Transactions on Scalable Information Systems,* vol. 9, no. 4, pp. 1-11, 2021.

[52] S. H. Khan, Z. Abbas and S. D. Rizvi, Classification of Diabetic Retinopathy Images Based on Customised CNN Architecture. In: "*2019 Amity International Conference on Artificial Intelligence (AICAI)*," IEEE, United States, pp. 244-248, 2020.

[53] Ö. F. Gürcan, U. Atıcı and Ö. F. Beyca, "A hybrid deep learning-metaheuristic model for diagnosis of diabetic retinopathy," *Gazi University Journal of Science,* vol. 36, no. 2, pp. 693-703, 2023.

[54] A. D. Hoover, V. Kouznetsova and M. Goldbaum, "(STARE)Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response," *IEEE Transactions on Medical Imaging,* vol. 19, no. 3, pp. 203-210, 2000.

[55] A. Vanita Sharon and G. Saranya, Classification of Multi-retinal Disease Based on Retinal Fundus Image Using Convolutional Neural Network. In: A. M. Iliyasu, R. Bestak, and F. Shi Eds. "*New Trends in Computational Vision and Bio-inspired Computing: Selected works presented at the ICCVBIC 2018, Coimbatore, India*," Springer International Publishing, Cham, pp. 1009-1016, 2020.

[56] R. Thanki, "A deep neural network and machine learning approach for retinal fundus image classification," *Healthcare Analytics,* vol. 3, p. 100140, 2023.

[57] A. Aljohani and R. Y. Aburasain, "A hybrid framework for glaucoma detection through federated machine learning and deep learning models," *BMC Medical Informatics and Decision Making,* vol. 24, no. 1, p. 115, 2024.

[58] S. Nawaldgi and Y. S. Lalitha, "Automated glaucoma assessment

from color fundus images using structural and texture features," *Biomedical Signal Processing and Control,* vol. 77, p. 103875, 2022.

[59] U. Ishtiaq, E. Abdullah and Z. Ishtiaque, "A Hybrid technique for diabetic retinopathy detection based on ensemble-optimized CNN and texture features," *Diagnostics (Basel),* vol. 13, no. 10, p. 1816.

[60] J. Verma, I. Kansal, R. Popli, V. Khullar, D. Singh, M. Snehi and R. Kumar. A Hybrid images deep trained feature extraction and ensemble learning models for classification of multi disease in fundus images. In: M. Särestöniemi, *et al.*, Eds., "*Digital Health and Wireless Solutions*," Springer Nature, Switzerland, pp. 203-221, 2024.

[61] M. M. Butt, D. A. Iskandar, S. E. Abdelhamid, G. Latif and R. Alghazo, "Diabetic retinopathy detection from fundus images of the eye using hybrid deep learning features," *Diagnostics,* vol. 12, no. 7, p. 1607, 2022.

[62] H. Xu, X. Shao, D. Fang and F. Huang, "A hybrid neural network approach for classifying diabetic retinopathy subtypes," *Frontiers in Medicine,* vol. 10, p. 1293019, 2024.

[63] B. Menaouer, Z. Dermane, N. El Houda Kebir and N. Matta, "Diabetic retinopathy classification using hybrid deep learning approach," *SN Computer Science,* vol. 3, no. 5, p. 357, 2022.

[64] A. Shamsan, E. M. Senan and H. S. A. Shatnawi, "Automatic classification of colour fundus images for prediction eye disease types based on hybrid features," *Diagnostics (Basel),* vol. 13, no. 10, p. 1758, 2023.

[65] "*Retina_Dataset*." Available from: https://github.com/yiweichen04/retina_dataset/tree/master [Last accessed on 2024 Sep 03].

[66] M. Londhe, "*Classification of Eye Diseases Using Hybrid CNN-RNN Models*," National College of Ireland, Dublin, 2021.

[67] M. H. Mahmoud, S. Alamery, H. Fouad, A. Altinawi and A. E. Youssef, "An automatic detection system of diabetic retinopathy using a hybrid inductive machine learning algorithm," *Personal and Ubiquitous Computing,* vol. 27, no. 3, pp. 751-765, 2023.

[68] J. K. Shimpi and P. Shanmugam, "A Hybrid diabetic retinopathy neural network model for early diabetic retinopathy detection and classification of fundus images," *Traitement du Signal,* vol. 40, no. 6, pp. 2711-2722, 2023.

[69] H. J. Sarode and D. Desai, "Customized mechanism for diabetic risk prediction: A Hybrid CNN–autoencoder approach with emphasis on retinal imaging in the elderly," *Journal of Electrical Systems,* vol. 20, no. 1s, pp. 190-199, 2024.

[70] K. Pin, Y. Nam, S. Ha and J. W. Han, "Deep Learning Based on Ensemble to Diagnose of Retinal Disease using Optical Coherence Tomography. In: "*2021 International Conference on Computational Science and Computational Intelligence (CSCI)*," pp. 661-664, 2021.

[71] I. Bouchrika, "*How to Write Research Methodology in 2024: Overview, Tips, and Techniques*," Available from: https://research.com/research/how-to-write-research-methodology [Last accessed on 2024 Sep 10].

[72] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke and A. Rabinovich, Going Deeper with Convolutions. In: "*2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*," pp. 1-9, 2015.

[73] K. He, X. Zhang, S. Ren, and J. Sun, Deep Residual Learning for Image Recognition, In: "*2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*," pp. 770-778, 2016.

[74] S. Aykat and S. Senan, "Advanced detection of retinal diseases via novel hybrid deep learning approach," *Traitement du Signal,* vol. 40, no. 6, pp. 2367-2382, 2023.

[75] D. S. Kermany, M. Goldbaum, W. Cai, C. C. S. Valentim, H. Liang, S. L. Baxter, A. McKeown, G. Yang, X. Wu, F. Yan,…& K. Zhang, "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning," *Cell,* vol. 172, no. 5, pp. 1122-1131.e9, 2018.

[76] D. Haase and M. Amthor, Rethinking Depthwise Separable Convolutions: How Intra-Kernel Correlations Lead to Improved MobileNets. In: "*2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*," pp. 14588-14597, 2020.

[77] [77] A. Howard, M. Sandler, B. Chen, W. Wang, L. C. Chen, M. Tan, G. Chu, V. Vasudevan, Y. Zhu, R. Pang, H. Adam and Q. Le, *et al.* Searching for MobileNetV3. In: "*2019 IEEE/CVF International Conference on Computer Vision (ICCV)*," pp. 1314-1324, 2019.

[78] M. M. Mafarja, D. Eleyan, I. Jaber, A. Hammouri and S. Mirjalili, Binary Dragonfly Algorithm for Feature Selection. In: "*2017 International Conference on New Trends in Computing Sciences (ICTCS)*," pp. 12-17, 2017.

[79] S. Mirjalili, "SCA: A Sine Cosine Algorithm for solving optimization problems," *Knowledge-Based Systems,* vol. 96, pp. 120-133, 2016.

[80] A. H. Al-Timemy, Z. M. Mosa, Z. Alyasseri, A. Lavric, M. M. Lui, R. M. Hazarbassanov, S. Yousefi, "A Hybrid deep learning construct for detecting keratoconus from corneal maps," *Translational Vision Science and Technology,* vol. 10, no. 14, p. 16, 2021.

[81] A. Nawaz, T. Ali, G. Mustafa, M. Babar and B. Qureshi, "Multi-class retinal diseases detection using deep CNN with minimal memory consumption," *IEEE Access,* vol. 11, pp. 56170-56180, 2023.

[82] M. A. Rodríguez, H. AlMarzouqi and P. Liatsis, "Multi-label retinal disease classification using transformers," *IEEE Journal of Biomedical and Health Informatics,* vol. 27, no. 6, pp. 2739-2750, 2023.

[83] C. Guo, M. Yu and J. Li, "Prediction of different eye diseases based on fundus photography via deep transfer learning," *Journal of Clinical Medicine,* vol. 10, no. 23, p. 5481, 2021.

[84] M. A. Syarifah, A. Bustamam and P. P. Tampubolon, Cataract classification based on fundus image using an optimized convolution neural network with lookahead optimizer. In: "*AIP Conference Proceedings*,"vol. 2296, no. 1, AIP Publishing, United States, 2020.

[85] G. Naik, N. Narvekar, D. Agarwal, N. Nandanwar and H. Pande, "Eye disease prediction using ensemble learning and attention on OCT scans. In: "*Future of Information and Communication Conference*," Springer, Germany, pp. 21-36, 2024.

[86] National Library of Medicine "*PubMed Database*." Available from: https://pubmed.ncbi.nlm.nih.gov [Last accessed on 2025 Feb 14].